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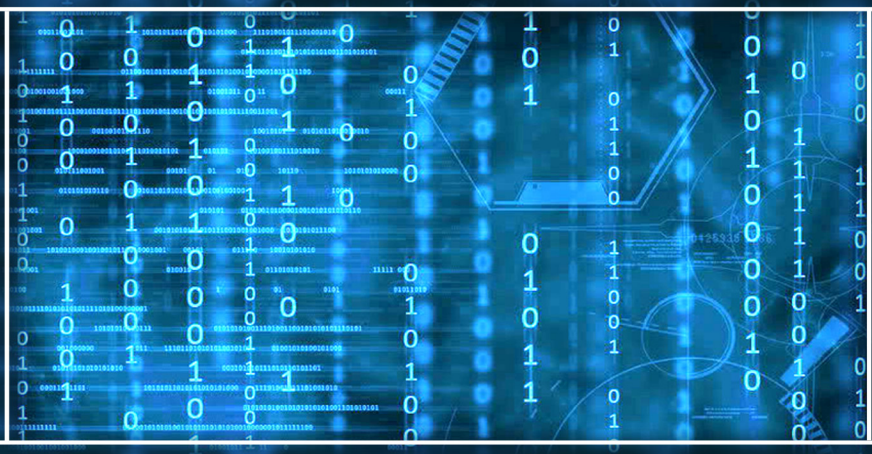

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# Editorial Preface

*From the Desk of Managing Editor…*

It may be difficult to imagine that almost half a century ago we used computers far less sophisticated than current home desktop computers to put a man on the moon. In that 50 year span, the field of computer science has exploded.

Computer science has opened new avenues for thought and experimentation. What began as a way to simplify the calculation process has given birth to technology once only imagined by the human mind. The ability to communicate and share ideas even though collaborators are half a world away and exploration of not just the stars above but the internal workings of the human genome are some of the ways that this field has moved at an exponential pace.

At the International Journal of Advanced Computer Science and Applications it is our mission to provide an outlet for quality research. We want to promote universal access and opportunities for the international scientific community to share and disseminate scientific and technical information.

We believe in spreading knowledge of computer science and its applications to all classes of audiences. That is why we deliver up-to-date, authoritative coverage and offer open access of all our articles. Our archives have served as a place to provoke philosophical, theoretical, and empirical ideas from some of the finest minds in the field.

We utilize the talents and experience of editor and reviewers working at Universities and Institutions from around the world. We would like to express our gratitude to all authors, whose research results have been published in our journal, as well as our referees for their in-depth evaluations. Our high standards are maintained through a double blind review process.

We hope that this edition of IJACSA inspires and entices you to submit your own contributions in upcoming issues. Thank you for sharing wisdom.

**Thank you for Sharing Wisdom!**

**Kohei Arai**
**Editor-in-Chief**
**IJACSA**
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# Editorial Board

# CONTENTS

# Augmented Sensory Experience and Retention: ASER Framework

Samer Alhebaishi[1], Richard Stone[2]
Human-Computer Interaction Department, Iowa State University, Ames, Iowa, USA[1]
Industrial and Manufacturing Systems Engineering Department, Iowa State University, Ames, Iowa, USA[2]

***Abstract*—In the process of shifting from traditional teacher-centred systems to more student-engagement ones, Augmented Reality (AR) is coming into its own as a way of improving how information is delivered and received. However, while the use of AR is commonly attributed to increasing engagement, the potential of this technology to support deep, long-term learning is not fully explored. The ASER Framework (Augmented Sensory Experience and Retention) offers a new approach to this gap by integrating emotional memory, interactive storytelling, and gamification within AR environments. After analyzing the current state of AR education research, this study found a lack of frameworks that combine these elements systematically, thus offering a chance to improve cognitive retention and meaningful learning. A multi-sensory model proposes ASER for emotional connection, participation, and knowledge consolidation. The theoretical foundation is strong; however, further empirical validation is required to determine its real-world effectiveness across diverse educational settings. These recommendations provide a starting point for future research and implementation strategies that seek to change the rules of instructional design for engaging and enduring learning experiences.**

***Keywords*—Augmented Reality (AR); emotional memory; interactive storytelling; gamification; Augmented Sensory Experience and Retention (ASER) Framework**

## I. Introduction

AR is changing the education system by providing real-world application of the theoretical concepts learned in the classrooms. In its simplest form, AR involves using digital information in the real world and, therefore, provides a way of making learning more practical, enjoyable and meaningful [1]. As pointed out by Alhebaishi, even though the use of AR in education has been found to improve students' engagement and understanding, the impact of AR on long-term memory is still unclear.

Current research has mainly focused on short-term cognitive results with little or no concern about how AR-based simulation can help in encoding and retrieval in the long run. Studies in emotional engagement reveal that the incorporation of emotional content in the learning context improves both the cognitive and memory processes [2]. According to Alhebaishi, emotional engagement helps to make a connection with the learning content and thus enhances the memory processes of encoding and retrieving. When AR experiences are created to elicit emotional responses from the user in the form of stories, narratives, or games, then the content becomes more meaningful and easily remembered. The absence of standardized tools for evaluating the effectiveness of AR in the retention of knowledge is a major research deficiency. This omission is crucial to guarantee that AR is applied not only as a fun way to learn but as a means of enhancing retention and understanding [3]. Thees have identified how AR can improve the learner's interest, passion, and the retention of the matter through the creation of holistic and complex learning environments [4]. The conventional way of teaching is passive and includes such processes as telling, demonstrating, or showing the students something, while AR provides an active way of learning where digital objects can be interacted with, problems can be solved, and instant feedback can be received [5].

Nevertheless, there are various advantages of AR in the educational sector, which are still waiting to be discovered and used in the process of identifying the most effective pedagogical strategies for deep learning and memorization. The biggest problem with AR learning is the absence of a framework that would integrate cognitive, affective, and motivational factors to optimize the learning process [3]. Conventional learning strategies may be unable to maintain students' interest and may also cause cognitive overload, resulting in poor long-term knowledge acquisition [6]. It is, therefore, important to suggest an integrated learning theory that incorporates AR together with other effective teaching strategies, not just for the purpose of achieving surface learning but for the production of meaningful, long-lasting learning experiences. In an attempt to fill this gap, the present framework proposes a new conceptual framework that integrates three core aspects: emotional memory, storytelling, and gamification. This study is guided by the following research question: How can a new augmented reality (AR)-based educational framework be designed to improve student engagement and enhance long-term knowledge retention in learning environments? To address this question, the ASER Framework is proposed as an integrative model that leverages emotional memory, storytelling, and gamification within AR environments.

Emotional memory has an important role to play in education because it is easier to encode and retrieve emotions than other types of information [7]. In this paper, it is suggested that AR can be used to induce emotions through narrative-based experiences and interactive components of the framework, which in turn improves the cognitive aspect of memory by creating an association between the learning content and emotions.

This connection is strengthened by interactive storytelling, which engages learners in meaningful environments where they can learn through stories [8]. Research in cognitive psychology has shown that narrative is an effective way of arranging information in a way that is easy to understand and remember [9]. When AR is incorporated into the storytelling process, the learners are no longer passive recipients but active participants, increasing cognitive involvement.

Gamification, which involves the use of elements such as reward, progress, competition, and real-time feedback to keep the learner motivated and engaged. Most famous for its capacity to enhance the fun and goal-directed aspect of learning, gamification enhances students' persistence and performance [10]. In the context of AR-based learning, it not only helps in the development of critical thinking and problem-solving but also encourages constructive learning attitudes through dynamic rewards and personalized learning paths [11].

Although these components—emotional memory for retention, storytelling for motivation, and gamification for engagement—are effective, not many AR educational models have incorporated two of them into good pedagogical practice. Despite the fact that each of these aspects has been investigated separately in previous research, no effort has been made to understand how they can be combined to achieve a moderate level of learner involvement in AR environments. The proposed framework solves this problem by presenting a systematic, empirically based framework that incorporates these three elements into a coherent framework for designing AR-based learning experiences. Based on cognitive science, educational psychology, and human-computer interaction, it provides a new perspective on how AR can solve some of the problems of conventional teaching methods.

This paper aims to describe the theoretical underpinning, the strategies for putting the framework into practice, and the expected results of the proposed framework, including the effects on student engagement, learning, and cognition. Furthermore, it outlines the current deficiencies of AR education and claims that integrating emotional memory, storytelling, and gamification can significantly improve the quality of learning experiences in various educational settings.

### A. Paper Organization

The remainder of this paper is organized as follows:

*1) Objective:* This section outlines the primary goal of the ASER Framework, emphasizing its role in enhancing long-term knowledge retention through emotional memory, storytelling, and gamification.

*2) Previous frameworks:* A review of existing AR-based educational models, discussing their strengths, limitations, and gaps that the ASER Framework seeks to address.

*3) Previous works:* This section explores related research on emotional memory, storytelling, and gamification, demonstrating their individual effectiveness in education.

*4) The Effect of background music on cognitive and emotional memory:* A discussion on the cognitive and emotional impact of background music and its potential role in enhancing memory retention.

*5) Introducing ASER framework:* This section presents the ASER Framework, its theoretical underpinnings, and how it integrates emotional memory, storytelling, and gamification.

*6) Framework overview:* An explanation of the structure and mechanisms of ASER, detailing how it enhances learning experiences.

*7) Core components:* A breakdown of the three fundamental elements—emotional memory, interactive storytelling, and gamification—illustrating their roles and interactions.

*8) Structured integration of background music, storytelling, and gamification:* This section describes how these components are systematically combined to maximize engagement and retention.

*9) Synergistic integration for enhanced learning:* Analyzing how the combined use of emotional memory, storytelling, and gamification creates a holistic and immersive learning environment.

*10)Layered approach to learning enhancement in AR: ASER framework:* A structured breakdown of ASER into the Theory Layer, AR Application Layer, and Outcome Layer, highlight-ing its implementation and impact.

*11)Conclusion:* A summary of the study's contributions, implications for educational practice, and directions for future research.

## II. Objective

The primary purpose of this framework is to develop a theoretical model that can be used to improve the learning effectiveness of techniques that aim to enhance the long-term memory of knowledge. This improvement could be achieved through the combination of cognitive load theory and the latest technological tools, such as emotional memory, interactive storytelling, and gamification techniques.

The framework aims to reveal new ways and means that can help to increase the impact of educational interventions, with a special emphasis on the role of emotional arousal and story-based instructions in the process of memory consolidation. With the help of these factors, the framework is to offer a more comprehensive view of education, to the exclusion of conventional teaching methodologies in the aspect of retaining information in the long run.

This framework is significant as it has the potential to change the way educational practices are carried out. By proposing a new way of thinking about the integration of technology and cognitive science, this framework aims to solve the problems of students' attention and memory, as well as the durability of learning outcomes. Its findings are especially significant in settings where traditional approaches have failed to deliver the desired results, thus calling for more creative and engaging ways of teaching and learning.

The originality of this framework lies in the fact that it establishes a theoretical basis for a new strategy of enhancing the retrieval of knowledge from long-term memory within the context of education, with the primary focus being on the cognitive and technological factors and not on the actual results. The concept of emotional memory and interactive storytelling as retention tools is a new perspective in educational research that the framework introduces. The framework is intended to stimulate further academic work, including discussion and development. In the end, the idea presented in this framework may help to inform further research and application, so that future educational interventions will be more innovative, effective, and memorable, and thus more likely to engage learners and improve memory retention.

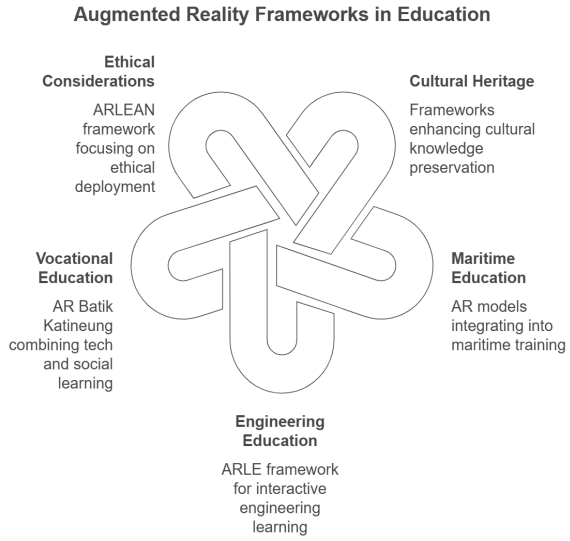


Fig. 1. An overview of various AR frameworks used for educational purposes [12] [13] [14].

## III. Previous Frameworks

Various fields have spanned the exploration of AR frameworks to offer innovative solutions to improve educational and professional practices. The framework developed by Innocente is used to leverage immersive XR technologies in the domain of cultural heritage [12]. This framework is based on a user-centred design approach in conjunction with the PRISMA guidelines to conduct a systematic review of XR applications. It greatly aided in the conservation and distribution of cultural information and delivered more immersive and engaging experiences for users to interact with historical information. In maritime education, Balcita and Palaoag proposed an AR model framework to incorporate AR technologies into conventional maritime training [13]. This framework provided practical skill development through the provision of practical simulations and realistic training scenarios, but it had some problems in the integration of the technology and the users' adaptation to it. In engineering education, Faridi also designed an ARLE framework which applied 3D models and mobile applications to build a 3D AR environment for learning [14]. The framework designed for the implementation of AR in the learning environment (ARLE) helped the students to learn, as they could interact with virtual objects and had a chance to visualize complex engineering concepts. Christopoulos and Mystakidis proposed the ARLEAN Ethical Framework for integrating learning analytics with educational technology [15]. It also highlighted the ethical issues that are associated with the use of AR technologies, leakage and hence bias, and balanced usage of technology in learning. In vocational education, AR was integrated, and Widiaty developed the framework of AR Batik Katineung [16]. The framework integrated technological skills with social learning skills to build a comprehensive curriculum that included both technical skills and cultural skills. Challenor also applied AR in cultural heritage education to design a framework that could enable storytelling to make historical and cultural content more engaging and accessible. This framework was intended to develop an emotional connection with the material to support knowledge retention and transfer [1]. These frameworks, therefore, demonstrate the varied uses of AR in different fields and how AR can be used to solve particular educational or professional problems (see Fig. 1). But they also have common challenges, such as the need for high-quality hardware, technical support, and equity. Further research should be done to overcome these challenges, improve the scalability, availability, and ethical implications of AR technologies and find new applications of AR in emerging fields to unleash the full potential of AR in learning and other industries.

## IV. Previous Works

Emotional memory is a critical factor that can help to make the learning process more effective within the AR environment. Number of studies also confirm the significance of emotional engagement in designing effective and engaging learning processes. In the study by Leinonen, emotional engagement was observed through collaborative storytelling. The connection between the stories and the emotional responses helped the children to learn and engage in the content more easily. The high emotional responses induced by this AR-based storytelling showed the effectiveness of emotional memory in the learning process [17]. In another important research, Muhammad explained how AR-based learning environments enhance motivation and emotional attachment to the content. This emotional engagement, which was facilitated by the interactive AR experiences, improved both the engagement and the retention of the content, which supports the role of emotional memory in educational contexts [6]. In museum environments, AR was found to significantly increase emotional connections and, therefore, knowledge retention. Gong established that AR provided an enhanced emotional experience through the physical interaction with the museum objects in order to improve the long term memory [5]. This effect was also observed

in the area of science education where AR was capable of acting as an emotional trigger to enhance students' academic achievement and retention of knowledge [18]. Furthermore, the real-time data analysis during the laboratory experiments using AR made the hitherto abstract concepts more tangible and emotionally appealing and thus helped in the retention of complex concepts. Thees also provided evidence for this effect by showing that the emotional connection to real-time data improved retention [4]. In Sabbah study, emotional engagement was linked to motivation, which in turn increased retention. Even though emotional memory was not directly measured, the ARCS-V model (which is based on attention, relevance, and satisfaction) showed that emotional interest made the learning experiences more meaningful and meaningful [19]. For instance, in Lai's study, immersive AR environments helped students to develop an emotional relationship with the content to improve retention through engagement.

In other cases, the emotional memory is implied indirectly through motivation and engagement results [20]. In addition, Aydogdu showed that AR-enhanced motivation and attention, producing interesting experiences that could well prove useful for future learning [21]. Amores, and Ciloglu also reported that AR could help students develop an emotional affinity towards the content and, in turn, improve their motivation and memory retention [22][23].

It is important to note that gamification is one of the most successful features of AR-based learning that has been used and proven to be effective in increasing motivation, engagement, and retention in various studies. It includes elements of the game, such as plot, mini-quizzes, and character actions, which increase the learner's motivation and help them remember the information better. For example, Li presents how a gamified AR environment with interactive storytelling increases retention by keeping the learners engaged.[8] In the same manner, Muhammad integrates quizzes and other interactive features into the learning process and reveals that gamification enhances both motivation and retention [6]. Syskowski establishes that the AR-based gamified elements in physics education increase students' interest, achievement, and participation.[24] Furthermore, Yoo argues that the gamified interactions in the AR environments increase the motivation and engagement of the learners and, therefore, improve retention of the content [25]. In the area of vocabulary learning, Belda found that gamified AR learning was more effective in retention and performance than the conventional method.[11] Furthermore, Delgado presented how motivation and student performance were enhanced through gamification in AR applications, leading to increased retention.[26] Lastly, in the area of chemistry, Liu shows that gamified AR experiences are engaging to students and thus improve retention [27]. This pattern holds across studies by Jdaitawi and elik where the immersive and gamified nature of AR enhances both learning and retention [10][28].

This paper aims to explore how storytelling helps enhance learners' sensory engagement, retention, and overall participation in the AR environments. As a pedagogical tool, storytelling acts as an anchor that helps learners connect with the content on an emotional level, thus ensuring that the content is well-committed in the long-term memory. In this paper, Sanchez shows that storytelling was an important factor that led to improved retention of the material through the development of emotional links with the learners [9]. This is in consonance with the findings of Li where dynamic and player-adaptive narratives helped in maintaining the attention of the learners and improving memory retention [8]. However, in AR, storytelling can be used to make the learning process more relevant and engaging, especially in language-learning classrooms. Ersanli found that AR applications that use narratives increased vocabulary learning because they were engaging [29]. Similarly, Zuo argued that the fantasy and real-life narratives in the game-based AR increase the cognitive engagement and memory retrieval [30]. In addition, it can be noted that in the process of reflective thinking and motivation, storytelling also plays a significant role. Sabbah also points out that AR-based storytelling tools can improve reflective thinking to positively influence learning [19]. In cultural heritage education, the stories are used to engage the learners in emotionally charged experiences. De Paolis established that the use of AR in storytelling increased engagement by offering detailed historical and cultural information [31]. Similarly, Singh stresses the role of interactive and adaptive narratives in the creation of immersive learning environments that enhance retention [32]. Not always the storytelling is the main focus in AR applications, but it is usually incorporated into them. Chen, reflective prompts were used to guide students through the learning process, acting as a narrative structure to help them understand and retain the learnt matter [33]. Sometimes, the storytelling elements are combined with traditional teaching methods. Despite the fact that some studies, for example, Christopoulos, do not include storytelling as a specific strategy, they employ immersive AR environments that provide narrative-like guidance through a sequence of learning tasks [34].

### *A. The Effect of Background Music on Cognitive and Emotional Memory*

Background music has been found to improve cognitive performance and the management of emotional memory in learning environments. Azmi's research also indicates that including Lo-Fi and classical music in the classroom improves attention, memory, and mood, which in turn creates a positive and productive learning atmosphere by decreasing stress in students. Instrumental music with a slow beat (60-80 BPM) was the best for tasks that require focus over a long period of time, while music with a moderate pace (80-100 BPM) was suitable for quick thinking and problem-solving. Background music should be played at a volume that does not interfere with the instructor's ability to convey information and should usually be between 30% to 40%[35]. Similarly, Rickard explored how relaxing music can be played after being exposed to emotionally charged content to help regulate memory recall. The study revealed that post-event music acted as a moderator of increased emotional memory consolidation, meaning that background music can be used to manage the emotional effects of learning [7]. This is also supported by Que, who investigated the effect of music on task performance and emotional control. The result of the research revealed that background music decreased students' level of frustration and improved their reading comprehension performance, thus revealing that music can be used to improve concentration during difficult tasks [36]. Last, Tyng explained how learning

is affected by music-induced emotions whether positive or negative. The study established that, by synchronising music with the emotional content of the material, memory retention and attention can be improved and that music can, therefore, be used to regulate mood to enhance learning [37]. Taken together, these studies suggest that the appropriate choice of background music can enhance learning by improving attention, decreasing anxiety, and shaping emotional responses. Thus, background music can be used by educators to produce an optimum learning environment and better emotional as well as cognitive development of the students.

## V. Introducing ASER Framework

The ASER Framework represents a novel approach to enhancing long-term knowledge retention in educational settings by integrating emotional memory, interactive storytelling, and gamification. Based on cognitive science and the latest developments in educational technologies, the framework seeks to improve both engagement and retention at the same time. The Previous Works section presents a demonstration of this through a review of the existing AR-based learning research, which reveals a significant absence of studies that simultaneously incorporate all three elements. Each of these elements, emotional memory, storytelling and gamification, have been shown to enhance learning on their own, but their joint use has not been well explored. This finding indicates a missed opportunity in the current AR education to fully tap into the potential for building rich, long-lasting and emotionally rich learning experiences. The ASER Framework fills this gap by proposing a unified model of these elements and recommending that future attempts should focus on more holistic integration for greater learning effectiveness.

### A. Framework Overview

To enhance knowledge retention, the ASER Framework uses the following approaches: Multi-sensory engagement, Emotional connection, and Interactive storytelling. The main purpose of this framework is to develop engaging and enjoyable ways of learning that cannot be achieved through conventional teaching. ASER Framework consists of several components that help to make the learning process more meaningful and easier to remember through the use of different senses, emotional engagement, and interesting stories. In this way, the ASER Framework seeks to enhance engagement and productivity in the learning process in order to enhance the retention of learned matter. To support cognitive development, ASER integrates Bloom's Taxonomy as a foundational structure for cognitive progression in AR-based learning environments(see Fig. 2). Hence, emotional memory assists in the acquisition of Knowledge and Comprehension, while interactive storytelling supports Application and Analysis, and gamification encourages Synthesis and Evaluation. Thus, through alignment with Bloom's hierarchical model of learning, ASER ensures that the educational interventions not only engage the learners in the immediate moment but also support the development of progressive and lasting cognitive growth.

### B. Core Components

*1) Emotional connection:* This component seeks to generate strong, lasting impressions by tapping into emotional

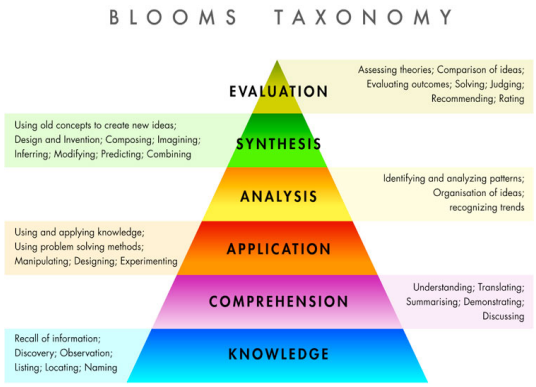


Fig. 2. Structure of bloom taxonomy [38].

memory. Emotions are powerful drivers of memory, and by incorporating emotionally resonant content [39], the framework helps learners connect with the material in a deeper way, making it easier to remember. Emotional memory is invoked through the use of background music, which makes the learning environment more engaging. Background music is used to help students make emotional connections with the content of the lesson in order to encourage emotional involvement. For instance, when teaching a chemistry lesson on chemical reactions, using energetic background music when showing an interesting experiment, for instance a color changing reaction, can help students feel more interested and emotionally involved in the activity. That means that emotional engagement enhances their attention, increases the depth of understanding, and facilitates the long-term storage of science concepts, including the difficult ones. Background music stimulates emotional responses that, in turn, enhance focus and understanding for better recall and learning (see Fig. 3). In this case, the emotional involvement serves to reinforce the learning material in the long-term memory and thus enhance both the retention and the satisfaction with the learning process.

Interactive Storytelling: This component uses the power of narrative to situate the content within a context. In addition, through the use of interactive storytelling, learners can learn about various scenarios and their possible outcomes while being an active part of the learning process. Not only does this make the material more fun for the students, but it also enhances their understanding and memory of the information. Interactive storytelling comes with a twist to make the stories more relatable and linked to the students' lives. Although the use of globally recognized stories is effective at first, they may not be enough to capture the attention of today's students, who are known to have a very short attention span and are easily distracted. In order to solve this issue, the lesson content is developed to include narratives that are similar to the students' lives thereby improving the learning concentration and memory. Storing familiar themes in a different way makes the storytelling process more interesting, thus engaging learners and helping them learn more easily [40]. This approach not only enhances the appeal of the lessons but also assists students in retaining information by relating it to their own experience and environment, thus making the learning process more effective and enjoyable (see Fig. 4).

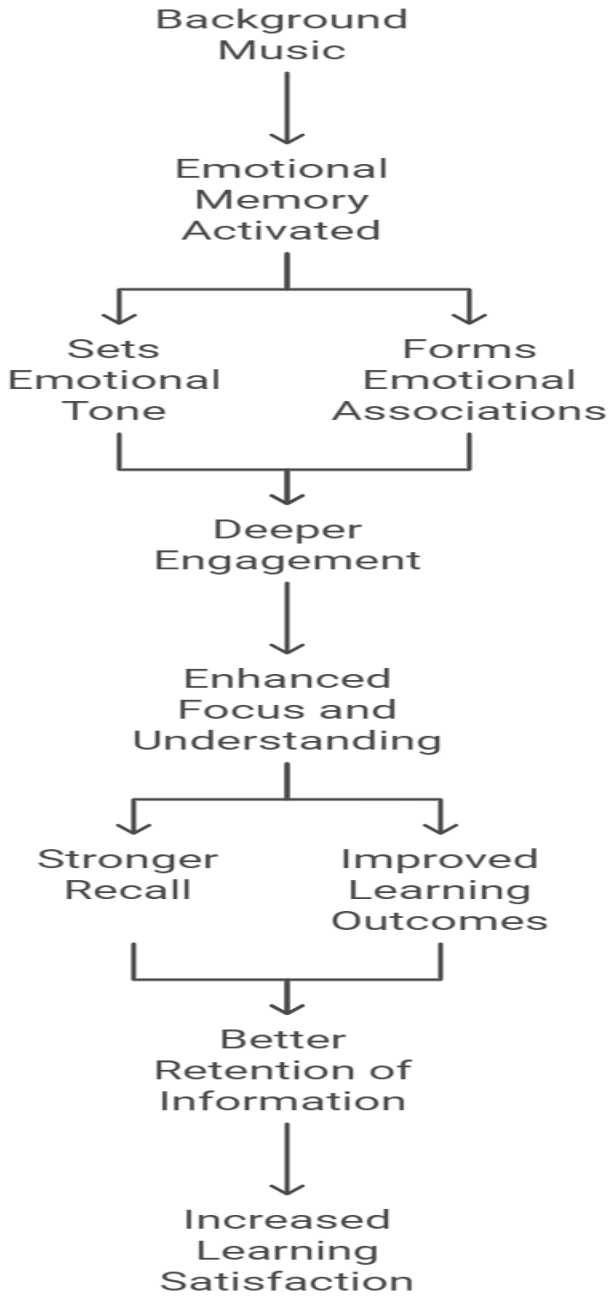


Fig. 3. Role of background music in activating emotional memory.

*2) Gamification:* ASER Framework has implemented gamification to enhance the process of transforming boring classroom activities into more interesting and engaging tasks that would make students want to participate and do their best in the process (see Fig. 5). In this approach, students get level-ups for giving the right answer in class, making it a fun process. All the level-ups are combined with motivational background music to make the experience even better for the students and increase their motivation. The combination of immediate reward and music makes the environment positive, and the students are likely to remain interested and want to improve their status.

However, if a student is struggling or gives a wrong answer,

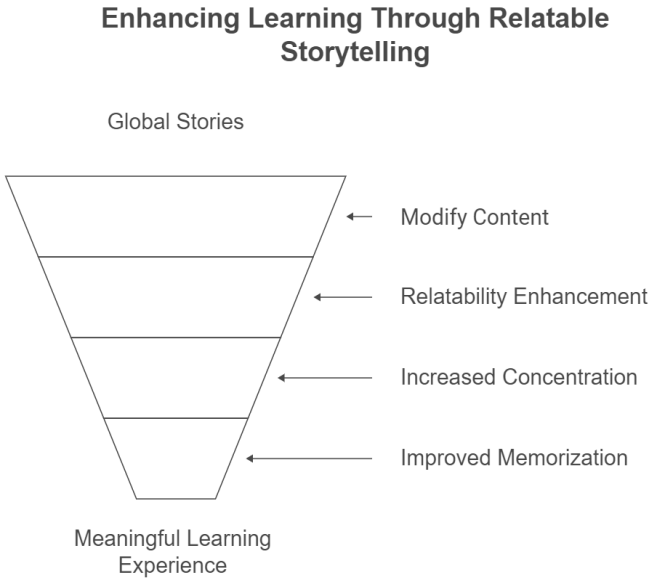


Fig. 4. Enhancing learning through relatable storytelling.

the framework uses another plan: Encouraging the student through gentle prompts and positive messages, not punishing them. This way, there is a more balanced approach between the positive and the negative aspects of the learning process, and the motivation is kept high throughout the lesson. In the meantime, students are encouraged to learn from their mistakes, which are considered as lessons rather than failures. This approach is based on the premise that mistakes are inevitable in the learning process and should be re-engineered as learning experiences from experiential learning theories to enhance understanding and memory in education [41]. In this case, the gamification elements are applied, and therefore, the classroom environment is similar to a game, which makes students more active, learn more and desire to improve themselves.

### *C. Structured Integration of Background Music, Storytelling, and Gamification*

The ASER Framework recommends using background music as an emotional trigger for memory in conjunction with interactive storytelling, which is supported by character-driven and narrative-based approaches. Enhanced with gamification elements like badges and music cues, it seeks to develop a more lively and engaging learning process. It is emotionally tuned through background music by prompting learning phases with motivator cues such as cheerful music during achievement intervals and calm music during introspection, which helps in recalling the different states associated with the critical points in the learning process. It enhances the focus, comprehension, and retention of the material since music helps in the formation of strong roots of cognitive and affective associations with the content [42]. The storytelling element includes three approaches that should be incorporated into the narrative structure of the project: Interactive Storytelling: It means that learners can make decisions that will affect the overall direction of the unfolding story, which will help to develop critical thinking and personalization of the learning

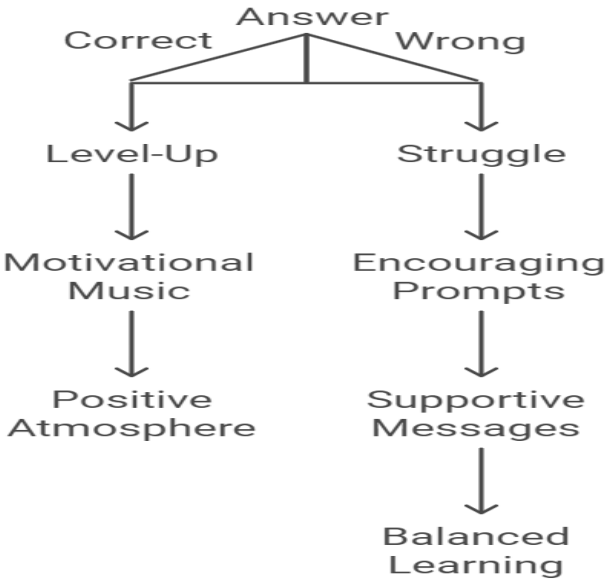


Fig. 5. Gamification response system in learning.

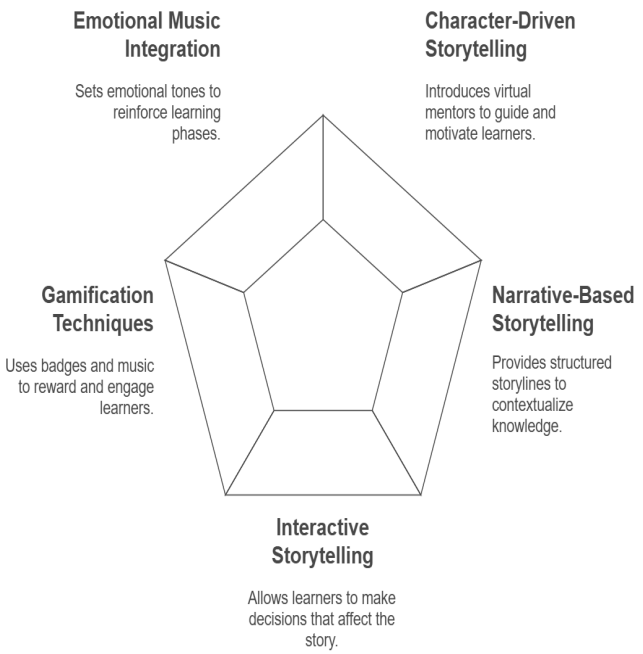


Fig. 6. Gamification response system in learning.

process. Narrative-Based Learning is a type of Learning in which a structured storyline is provided to learners so that their knowledge acquisition becomes contextualized and meaningful; Character-driven storytelling: The use of virtual mentors and companions to provide mentoring, encouragement, and real-time feedback. Gamification: ASER also incorporates elements of gamification, say, through the use of different badges and achievements to motivate learners to achieve challenges, a clear performance tracking system to update the learners on their performance in real-time, and music cues to engage, motivate, and create an emotional connection to the learning content (see Fig. 6). These all combine to create a synched up, dynamic, and emotionally charged learning environment, which should in turn lead to better engagement, a more profound understanding, and improved long term retention.

### *D. Synergistic Integration for Enhanced Learning*

The three components must be cohesively integrated to achieve the intended outcomes; emotional connection is activated through background music, which is strategically used at key moments to match the lesson's emotional content, aiding memory recall. This approach uses tempo, rhythm and tone variations to engage emotion and link content to long-term memory, making the learning process more engaging and personalised. Interactive storytelling also helps to place the material in context and uses engaging, relatable narratives that can be customised to students' responses. These narratives are based on real-life situations that students can easily relate to, hence making the content easy to comprehend. Also, role play and virtual storytelling are active participation tools, while narrative-based assessments enhance understanding. Gamification makes most classroom activities fun and engaging tasks that students learn from by turning them into games complete with a level-up system and instant feedback. In order to use this framework effectively, teachers need to be trained to include music, storytelling, and gamification into their teaching and adjust them to the specific situation in the classroom. Online resources can help to integrate the various elements easily, and feedback from students and analysis of data can help refine the components of the framework for maximum learning benefit (see Fig. 7). Thus, specifying the criteria for evaluating the effectiveness of ASER Framework in enhancing retention, engagement, and emotional learning, it is possible to create a framework that would not only help students learn better in the short term but also retain the information and enjoy the learning process more.

## VI. Layered Approach to Learning Enhancement in AR: ASER Framework

ASER Framework employs a multi-layered approach to maximize learning engagement and retention within AR environments. This approach integrates three main layers:

### *A. Theory Layer*

*1) Foundation of learning enhancements:* This layer includes the basic theoretical concepts— emotional memory, storytelling, and gamification, which are the basis of the ASER Framework. These components are critical in the development of an effective and interesting learning process and thus form the basis of a more holistic approach.

### *B. AR Application Layer*

*1) Implementation of the theory in practice:* This layer focuses on the real-life use of the theory in the AR environment,

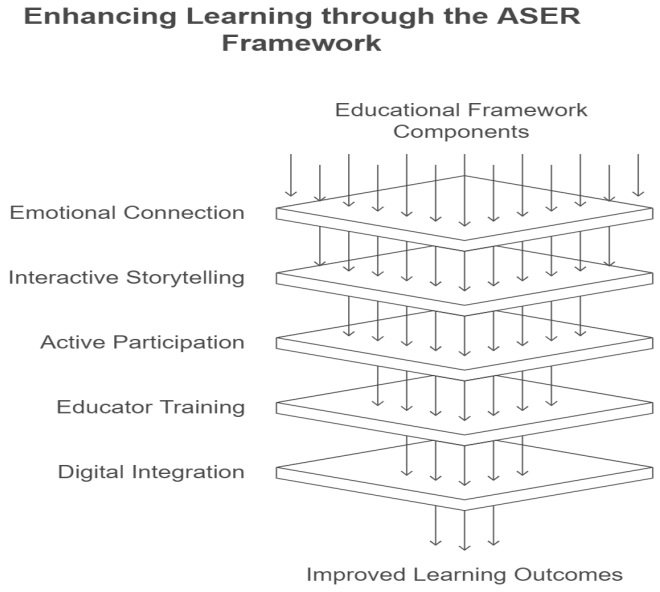


Fig. 7. Multi-Layered ASER framework for enhancing learning.

with the help of various elements to make the place come to life. Emotional memory is stimulated by the background music, storytelling is linked to the students' real-world situations, and gamification makes learning more fun and rewarding. These strategies in combination help to capture and maintain learners' attention and focus, as well as encourage them to remember information while being in the AR environment.

### C. Outcome Layer

*1) Analyzing the learning effect:* This last layer looks at the results of the framework, which measures the students' learning, retention, and participation. Based on the work of Bloom, this layer uses the taxonomy as a way of measuring the cognitive gain and for the development of higher-order thinking skills and thus the success of the framework in the attainment of both acute and future learning results.

The evaluation process starts with identifying whether students are able to recall and understand concepts introduced through the AR-based storytelling so they have learned the basic facts. Then students are tested on their ability to apply and analyze this information by solving problems or making decisions within the AR environment, thus showing more complex thinking. Last, the evaluation and creation levels of Bloom's Taxonomy are addressed by requiring students to think about their learning experience and come up with their own ideas and solutions based on what they have learned in the immersive environment. This is a systematic way of ensuring that the ASER Framework does not only improve on the rates of learning and retention but also the development of critical thinking skills thus providing for a more effective and impactful learning process (see Fig. 8).

By integrating these layers, ASER Framework provides a structured, immersive learning experience that connects theory, practical application, and evaluation, ultimately enhancing both engagement and long-term retention.

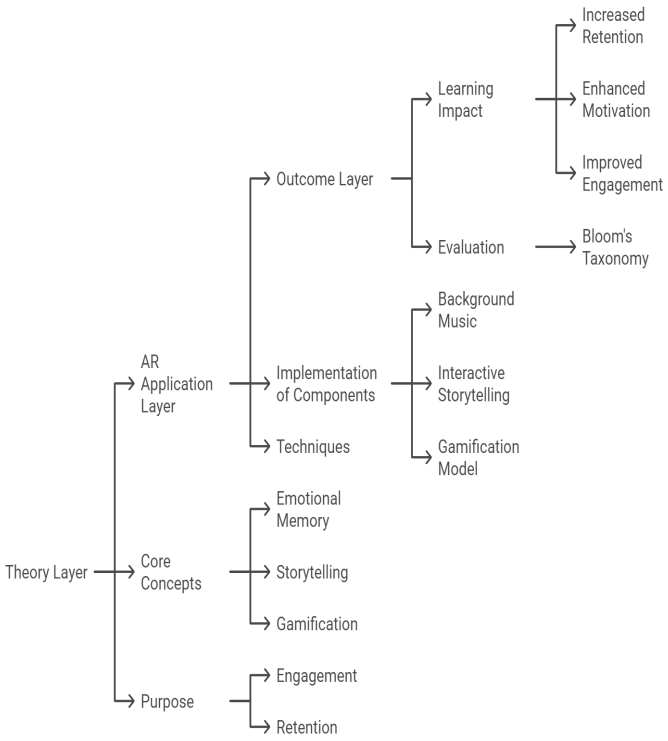


Fig. 8. The structure of ASER framework.

## VII. Conclusion

The ASER Framework is a theoretical framework that was proposed to change the way we deliver educational experiences with the help of emotional memory, storytelling, and gamification within the AR environment.

The paper identifies a significant research gap in the integration of emotional memory, storytelling, and gamification in AR-based educational environments, thus signaling a possibility to enhance the application of AR in education. Through the integration of these elements, the ASER Framework seeks to overcome the limitations of current educational practices and offer learners greater emotional involvement, contextualization through stories, and playfulness.

ASER Framework has been postulated as a theoretical framework to stimulate the development of subsequent studies and the creation of more sophisticated AR applications that integrate all three components.

The possible directions for future research can be connected with the implementation of this framework in various educational settings, evaluating its effectiveness for various users, subjects, and settings. Thus, the ASER Framework can be considered as a starting point for the enhancement of educational practices and, therefore, as a way of enhancing the quality, usability, and duration of the learning process. By addressing potential challenges such as technology accessibility and educator training, the ASER Framework can serve as a foundation for advancing educational practices, ultimately leading to more sustainable, engaging, and effective learning outcomes.

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# Comparing Vision-Instruct LLMs, Vision-Based Deep Learning, and Numeric Models for Stock Movement Prediction

Qizhao Chen
Graduate School of Information Science, University of Hyogo, Kobe, Japan

***Abstract*—This research conducts a comparative study of several stock movement prediction approaches, evaluating large language models (LLMs) and vision-based deep learning models with stock image as input, as well as models that utilize numerical data. Specifically, the study investigates a prompt-based LLM framework that processes candlestick charts, comparing its performance with image-based models such as MobileNetV2, Vision Transformer, and Convolutional Neural Network (CNN), as well as models with numerical inputs including Support Vector Machine (SVM), Random Forest, LSTM, and CNN-LSTM. Although LLMs have demonstrated promising results in stock prediction, directly applying them to stock images poses challenges compared to numerical approaches. To address this, this study further improves LLM performance with post-hoc calibration, reducing prediction biases. Experimental results demonstrate that post-hoc calibrated LLMs with visual input achieve competitive performance compared to other models, highlighting their potential as a viable alternative to traditional stock prediction methods while simplifying the prediction process.**

***Keywords*—Convolutional Neural Network (CNN); Large Language Model (LLM); MobileNetV2; stock price prediction; time series forecasting; vision transformer**

## I. Introduction

Forecasting stock price movements has long been a crucial area of research in financial markets. Recent developments in machine learning and deep learning have led to significant improvements in predictive models, allowing better identification of market patterns. Machine learning models, such as decision tree [1], [2] and logistic regression [3], [4], and deep learning frameworks, such as LSTM [5], CNN [6], and transformers [7], have shown great promise in improving the accuracy of stock price forecasts. By leveraging vast amounts of historical price data, technical indicators, and external factors such as news sentiment, these models can capture the non-linear and complex nature of financial markets.

More recently, Large Language Models (LLMs), originally developed for natural language processing (NLP), have been explored in financial forecasting due to their ability to analyze large volume of unstructured text data, such as news articles, financial reports, and social media sentiment [8]. Although LLMs have shown promise in understanding market sentiment and extracting insights from textual data [9], their direct application to visual financial data, such as candlestick charts, remains a challenge. Unlike numerical or text-based input, stock charts require an understanding of spatial and temporal patterns, which LLMs are not inherently designed to process.

Candlestick charts are important tools in technical analysis and they show price changes and movements over time for a stock. Traditionally, their interpretation has to rely on human expertise such as traders or investment analysts. Later, image-based deep learning models such as Convolutional Neural Network (CNN) are used to process and analyze the charts. Nowadays, with the rapid development of LLMs, the interpretation of the candlestick charts can be performed by LLMs. However, integrating prompt-based LLMs for candlestick chart analysis is still an emerging field, and their effectiveness is limited by biases in prediction confidence. Moreover, imbalanced input data poses another challenge. Sometimes, the stock time-series data includes more upward movements than downward movements. However, using traditional resampling techniques might disrupt the temporal dependencies inherent in the data. Therefore, without proper adjustments, LLMs applied to stock images may generate inconsistent or unreliable forecasts, reducing their practical utility in financial decision making [10].

To overcome these limitations, this research proposes a post-hoc calibration framework to improve the reliability of LLM-driven stock movement predictions. Post-hoc calibration techniques, such as Platt Scaling, Isotonic Regression, and Temperature Scaling, are commonly used to refine probabilistic outputs in machine learning models, particularly in classification tasks. By applying these calibration methods to LLM-generated predictions, the LLM performance can be further improved.

Furthermore, if the performance of prompt-based LLMs with post-hoc calibration proves effective, the stock price prediction process can be further simplified. Compared to traditional deep learning models such as CNNs or ViTs, which require extensive feature engineering, LLMs can automatically process raw data with minimal preprocessing. In addition, LLMs not only analyze visual input, but also use their pre-trained knowledge to gain a deeper understanding of financial markets.

Another key objective of this paper is to compare an image-based approach, which uses candlestick charts as input, with a numerical value-based approach for stock price prediction. This comparison is particularly important, as prior research has primarily focused on either visual or numerical data separately, without directly evaluating their relative effectiveness. This analysis offers new insights into the advantages and limitations of each method, contributing to a more comprehensive understanding of their respective impacts on stock prediction accuracy.

The main contributions of this paper are listed below.

- This paper conducts a comparative analysis of LLMs with advanced image-based models, such as MobileNetV2, and numerical input-based models, such as LSTM, in stock movement prediction. The findings highlight that LLMs, when calibrated with visual inputs, can not only simplify the prediction process, but also achieve competitive or superior performance. This demonstrates the potential of prompt-based LLM approaches as an effective alternative to traditional deep learning models for stock market prediction.
- This paper introduces a post-hoc calibration framework designed to improve the accuracy of LLM-generated stock forecasts by using models such as LLaMA and Qwen. This approach refines raw predictions by adjusting for potential biases and inconsistencies, ultimately improving the reliability and robustness of LLM-driven market forecasting.
- This paper also examines the impact of data augmentation techniques on stock image data and finds that proper application of techniques such as rotation and zooming can enhance the performance of deep learning models such as MobileNetV3.

The remainder of this paper is structured as follows. Firstly, related work is listed in Section II. The methodology is then described in Section III. In Section IV, the experimental results are presented. Section V provides a discussion of the results. Finally, Section VI concludes the paper.

## II. Related Work

### A. Stock Prediction Using Technical Indicators and Sentiment Analysis

Technical indicators, derived from historical price and volume data, are widely used to forecast stock movements. For example, Agrawal et al. [11] apply optimal LSTM together with several technical indicators such as the relative strength index (RSI) and moving average (MA) to predict the price of the stock. Moodi et al. [12] investigate various feature selection techniques to identify the most relevant indicators to predict stock prices. Julian et al. [13] apply Multilayer Perceptron with technical indicators and day-shifting method to predict the stock price.

Beyond numerical indicators, financial sentiment plays a crucial role in stock forecasting. NLP techniques have been widely used to analyze financial news, social media discussions, earnings reports, and analyst opinions. Studies have shown that combining technical indicators with sentiment analysis improves prediction accuracy, as stock prices are influenced by both market trends and investor sentiment [9], [14], [15]. For example, Vargas et al. [16] use deep learning models, including CNN and LSTM, to predict stock market movements by integrating technical indicators with financial news headlines. Khairi et al. [17] utilize a combined approach that integrates technical indicators, fundamental data, and news sentiment to predict stock prices.

### B. Post-Hoc Calibration for Prediction Models

Deep learning models, particularly neural networks, often produce overconfident predictions, which can be problematic in high-stakes applications such as financial forecasting. Post-hoc calibration techniques address this issue by adjusting probability scores after model training, ensuring that confidence levels align more accurately with real-world probabilities. Rahimi et al. [18] present a method for post-hoc calibration of neural networks using a novel approach called g-Layers and also provides a theoretical support of post-hoc calibration methods. Furthermore, inspired by the concept of post-hoc calibration, Chen [19] applies Proximal Policy Optimization (PPO) to adjust the LLM-predicted output to improve the model performance.

### C. Image-Based Stock Prediction

Compared to numerical features, stock images are less commonly used in stock price prediction. However, some researchers have explored using images as inputs. For example, Steinbacher [20] approaches stock price movement prediction as an image classification problem using CNN model. The study converts financial time series data into images and applies image classification techniques to predict stock price movements. Bang and Ryu [21] apply CNN to predict stock price using stock images but the prediction accuracy is only around 50%. Zhou et al. [22] propose a hybrid framework that integrates an LLM, a Linear Transformer (LT), and a CNN model to forecast stock price. CNN is used to extract features from stock image data. Jin and Kwon [23] study how stock chart characteristics impact the stock price prediction via CNN and they find that the prediction accuracy is improved when using solid lines, color, and a single image without axis marks.

### D. Prompt-Based LLM Approach

The prompt-based approach has several advantages. For example, the prompts can be rapidly adjusted to meet the specific needs of the research, allowing for fine-tuning of the model's output to align with the desired results. This flexibility makes it easier to tailor the model's responses for different tasks, ensuring that the outputs are both relevant and precise for the research objectives. Some researchers have applied the prompt-based LLM approach in financial tasks. For example, Chen and Kawashima [9] use a prompt-based approach to compare the performances of several LLMs in financial sentiment analysis. Yang et al. [8] propose a FinGPT model, which is trained on financial data, including news, reports, and market data. Different prompts can be used to perform various tasks in finance.

As mentioned earlier, most existing studies focus exclusively on either image-based approaches or methods that utilize only numerical data for stock price prediction. The relative effectiveness of these two approaches remains unclear. In addition, strategies to enhance the vision-instruct LLM framework for stock forecasting have not been explored in previous research. This study aims to address these gaps in the current literature.

## III. Methodology

Fig. 1 shows the whole picture of this study. For LLMs (LLaMA and Qwen) and image-based deep learning models such as MobileNetV3, candlestick charts generated using the historical stock data are used as input. For other models such as SVM, numerical stock data are directly used as input. Stock movement (Up or Down) prediction made by each model will be used for comparison.

### A. Data

Daily stock price data for Apple, Tencent, and Toyota, spanning from 01/05/2015 to 08/05/2024, is retrieved from Yahoo Finance using the Python library yfinance. The data for each stock include the columns "Open", "Close", "High", "Low", and "Volume".

Candlestick charts, with a sliding window size of 20 days, are generated from stock price data using the Python library mplfinance to predict the stock movement (Up or Down) over the next five days. Volume data are incorporated below the candlestick chart to provide insight into trading activity. A sample of the image input is shown in Fig. 2.

### B. LLM Model Setup

In this study, two advanced LLMs are utilized: Llama-3.2-11B-Vision-Instruct and Qwen2-VL-7B-Instruct. Both of these models were released in 2024. Llama-3.2-11B-Vision-Instruct, developed by Meta, is designed for visual recognition, image reasoning, captioning, and answering general questions about images. According to Meta, this model outperforms many existing open-source and proprietary multimodal models on common industry benchmarks. Qwen2-VL-7B-Instruct, part of the Qwen series developed by Alibaba Cloud, is also an instruction-following model.

Both models are fine-tuned using ground-truth market movements derived from historical stock prices. For this process, 80% of the image data is allocated for fine-tuning, while the remaining 20% is reserved for validation. The Unsloth Python library is employed for fine-tuning, enabling faster training speeds with reduced memory consumption. The model input will be structured as follows (Table I).

TABLE I. LLM Input Format

```
[
{"role": "user",
"content": ["type": "text", "text": prompt,
"type": "image", "image": candlestick chart ],
{"role": "assistant",
"content": ["type": "text", "text": answer ],
]
```

### C. Baseline Models

All models are fed with input (images or numerical values) with a sliding window size of 20 days to predict the stock prices over the next five days. Image-based models include MobileNetV2, Vision Transformer (ViT) and CNN. Models with numerical inputs include SVM, Random Forest, LSTM, and CNN-LSTM.

MobileNetV2, ViT and CNN are three prominent deep learning architectures that have shown effectiveness in various computer vision tasks, including image classification, object detection, and stock market prediction based on candlestick charts. Each of these models has distinct characteristics that make them suitable for different aspects of financial time-series forecasting through visual representations.

- MobileNetV2: MobileNetV2, proposed by study [24], is a CNN model designed to optimize performance on mobile platforms. It uses an inverted residual structure, where the residual connections are placed between the bottleneck layers. The intermediate expansion layer employs efficient depthwise convolutions to filter features, introducing non-linearity. In general, the MobileNetV2 architecture includes an initial convolutional layer with 32 filters, followed by 19 residual bottleneck layers. The MobileNet model used in this study is a pre-trained model available in the torchvision library.
- Vision Transformer: ViT, proposed by study [25], represents a paradigm shift in deep learning for image analysis by leveraging self-attention mechanisms instead of convolutions. Unlike CNNs, which rely on local receptive fields, ViT processes input images as sequences of non-overlapping patches and applies a transformer-based architecture to capture long-range dependencies. The ViT model used in this study is based on the pre-trained "google/vit-base-patch16-224" architecture from Hugging Face. The model utilizes $16 \times 16$ image patches and processes them through a transformer encoder to capture spatial dependencies.
- Convolutional Neural Networks: CNNs remain a fundamental approach in image-based analysis due to their hierarchical feature extraction capabilities. CNNs utilize convolutional layers to learn spatial hierarchies of features, ranging from low-level edges to high-level structures. This characteristic allows CNNs to effectively capture essential visual elements within candlestick charts, such as trend lines, support and resistance levels, and reversal patterns. The CNN used in this study consists of two convolutional layers: the first with 32 filters of size $3 \times 3$, followed by ReLU activation and max pooling, and the second with 64 filters. The feature maps are flattened and passed through a fully connected (FC) layer with 128 neurons, activated by ReLU. The final FC layer outputs a single neuron with a sigmoid activation.

Furthermore, models with numerical inputs such as SVM [26], Random Forest [27], and LSTM [28], [29] are widely used in stock price prediction. Hybrid models such as CNN-LSTM are also popular candidates [30].

- Support Vector Machine (SVM): SVM is a supervised learning algorithm used for classification and regression tasks. The main logic behind SVM is to find the optimal hyperplane that maximizes the margin between different classes in the feature space. The kernel used in SVM in this paper is Radial Basis Function (RBF).

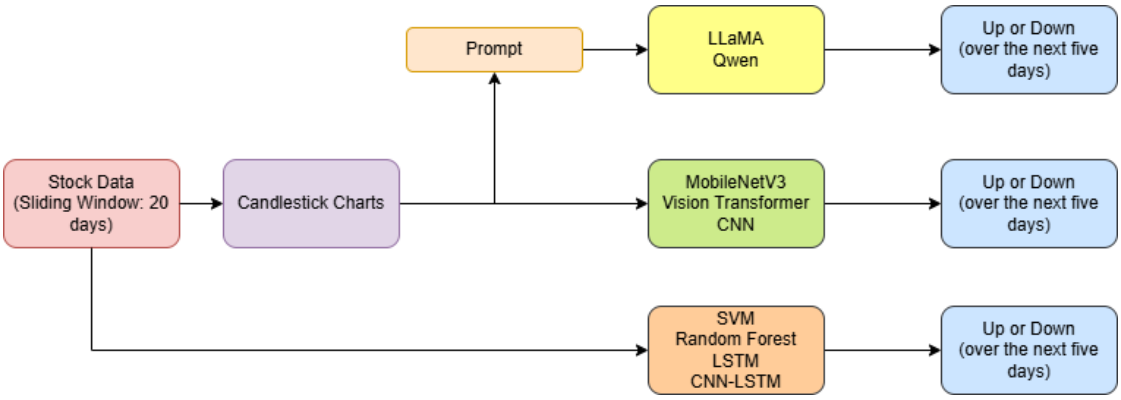


Fig. 1. Whole picture of this study.

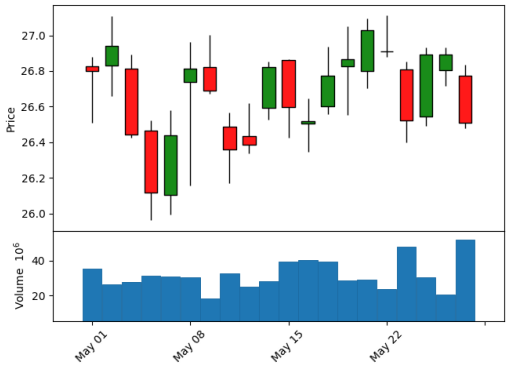


Fig. 2. Candlestick chart input sample.

- Random Forest: Random Forest is an ensemble method, which combines several decision trees to improve prediction accuracy. Each tree is trained on a subset of the data and makes independent predictions, which are then averaged (for regression) or voted on (for classification) to form the final output.
- LSTM (Long Short-Term Memory): LSTM is one type of recurrent neural network (RNN) and is originally designed to handle sequential data. It is particularly effective in capturing long-term dependencies due to its unique architecture, which includes memory cells that can retain information over time.
- CNN-LSTM: CNN-LSTM is a hybrid deep learning model that combines CNN and LSTM to capture both spatial and temporal dependencies in data. CNN excels at extracting spatial features from input sequences, such as images or time series data, by identifying local patterns through convolutional operations. These extracted features are then passed to an LSTM network, which is effective in modeling long-term dependencies and sequential relationships. This combination allows CNN-LSTM models to leverage both feature extraction and sequence learning. In this study, CNN-LSTM is fed with numerical values only.

### D. Prompt Design

A structured prompt is created to guide the LLMs in forecasting the stock movement. Table II shows an example of the prompt. This prompt instructs LLMs to identify market trends by analyzing technical indicators and market sentiment, and to provide the predicted market trend along with its probability, which can then be used for post-hoc calibration.

TABLE II. PROMPT FOR STOCK PRICE PREDICTION

Analyze the provided 20-day candlestick chart of company_name and predict the stock price movement within the next five days.

**Key Analysis Points:**

- **Technical Indicators:** Assess trends using SMA, EMA, RSI, MACD, Bollinger Bands, and volume changes. Highlight any crossovers, divergences, or extreme values.
- **Candlestick Patterns:** Identify bullish or bearish patterns (e.g., engulfing, doji, hammer, shooting star) and explain their significance.
- **Support/Resistance Levels:** Pinpoint recent highs, lows, and key price levels acting as support or resistance.
- **Market Sentiment:** Consider overall sentiment from recent news, earnings reports, or macroeconomic events that could influence the stock price.

**Output Format (JSON):**

```
{
  "prediction": "Up" | "Down" | "Same",
  "probabilities": {
    "Up": 0.XX,
    "Down": 0.XX,
    "Same": 0.XX
  },
  "justification": "Technical indicators
  (e.g., RSI at 70 indicates overbought),
  patterns (bullish engulfing),
  support/resistance levels,
  and market sentiment
  (positive due to strong
  earnings report)."
}
```

### E. Post-Hoc Calibration Techniques

Post-hoc calibration is a technique used to adjust the confidence scores of a machine learning model after training to better reflect the true likelihood of predictions. Many deep learning models, particularly neural networks, tend to be overconfident or underconfident in their outputs. Calibration methods help align the predicted probabilities with actual observed frequencies, making the model's confidence scores more reliable for decision-making.

To mitigate prediction biases and improve confidence estimation, one of the post-hoc calibration methods, Platt Scaling is used in this paper. Platt Scaling uses a logistic regression model to train on the model's logits to recalibrate probability outputs.

### F. Evaluation Metrics

The models are assessed based on accuracy, precision, recall, and F1 score. Accuracy represents the proportion of correct predictions made by the models. Precision quantifies the percentage of predicted positive instances that are truly positive, emphasizing the reliability of positive predictions. Recall, in contrast, measures the number of actual positive cases that the model correctly classifies. The F1 score is the harmonic mean of precision and recall. This metric balances the importance of precision and recall.

## IV. Results

The experimental results (Table III) present two LLMs, LLaMA and Qwen, with image-based deep learning models and models with numerical inputs in the context of stock price prediction using candlestick charts. The evaluation is conducted across three different stocks, Apple, Tencent, and Toyota, while also examining the impact of Platt Scaling calibration on the performance of LLMs.

In general, LLMs demonstrate strong predictive capabilities, particularly when calibration techniques are applied. LLaMA and Qwen show noticeable improvements in accuracy, precision, recall, and F1 score when Platt Scaling is used, suggesting that post-hoc methods can enhance their reliability. For example, in the case of Apple, LLaMA's accuracy increases from 0.79 to 0.86 after applying Platt Scaling, while its recall reaches 0.98, indicating a significant improvement in sensitivity to positive cases. Similarly, Tencent and Toyota also exhibit improved results for LLMs with calibration, reinforcing the effectiveness of adjusting confidence scores to refine predictions.

Among the image-based deep learning models, CNN consistently achieves strong performance across all stocks and often surpasses MobileNetV2 and Vision Transformer. Its ability to capture patterns in candlestick charts is evident, particularly in recall and F1 score, where it frequently outperforms other models. For example, CNN achieves an F1 score of 0.90 for Tencent and 0.88 for Toyota, demonstrating its robustness in financial time series analysis. MobileNetV2, although achieving competitive accuracy and recall, lags slightly behind CNN in precision. Vision Transformer, on the other hand, struggles in certain scenarios, particularly in recall, which indicates potential difficulties in recognizing crucial patterns in candlestick charts.

For models utilizing numerical inputs, CNN-LSTM demonstrates consistently strong performance, particularly in predicting stock movements for Apple and Tencent. It achieves high precision and recall, resulting in impressive F1 scores of 0.96 and 0.92, respectively. These results highlight the model's ability to effectively capture both spatial and temporal dependencies in financial data. However, its performance on Toyota is significantly weaker, with a recall of just 0.65 and an F1 score of 0.74, suggesting that the model may struggle with certain datasets or exhibit sensitivity to stock-specific characteristics. Furthermore, SVM, Random Forest, and LSTM perform similarly across stocks, with accuracy ranging from 0.73 to 0.77.

For an overall comparison, when predicting stock movement over the next five days, image-based models generally outperform those using numerical input, particularly CNN and LLaMA with post-hoc calibration, which achieve higher accuracy, precision, and recall.

For LLMs, the impact of calibration is particularly obvious. Without calibration, LLMs can generate competitive results, but their recall tends to be lower, which could lead to misclassification of important stock movements. The application of Platt Scaling addresses this issue by refining the decision boundaries, ultimately leading to a more balanced performance.

## V. Discussion

During the training of deep learning models such as MobileNetV2, high training accuracy is observed alongside significantly lower testing accuracy, which indicates a potential overfitting issue. To mitigate this issue, this study tries to apply some data augmentation techniques and examine how the model performances will change by using different methods.

Data augmentation is a technique to improve the diversity of training data and reducing the risk of overfitting in deep learning models. Among the commonly used techniques of image data augmentation, **rotation** helps the model adapt to slight variations in chart orientation. **Flipping**, particularly horizontal flipping, allows the model to recognize patterns in different orientations while preserving the underlying price movement structure. **Zooming**, on the other hand, modifies the scale of the candlestick chart, enabling the model to capture different levels of detail within the image and potentially identify subtle but important trading signals. The effectiveness of these augmentation strategies in improving model performance is reflected in Table IV, which presents the results of MobileNetV2 in Toyota's stock movement prediction under different augmentation scenarios.

The results demonstrate interesting insights into how different augmentation strategies impact the model's accuracy, precision, recall, and F1 score.

When rotation is applied, the model's accuracy improves to 0.80, the highest among all tested configurations. The recall also increases significantly to 0.95, which suggests that model becomes better at identifying positive cases, which is crucial for stock price prediction. The F1 score rises to 0.89, indicating a better balance between precision and recall. This improvement highlights the effectiveness of rotation in making the model more robust to variations in the input data.

Flipping augmentation does not improve accuracy, which is still at 0.73, similar to the no-augmentation case. However, there is a slight increase in recall to 0.87 and an F1 score of 0.85, suggesting that flipping might help the model capture more positive instances without significantly affecting precision.

Zooming improves accuracy to 0.78, with a recall of 0.94 and an F1 score of 0.88. This means zooming helps the model

TABLE III. EXPERIMENTAL RESULTS FOR DIFFERENT MODELS ACROSS THREE STOCKS

| Stock | Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|
| Apple | LLaMA | 0.79 | 0.85 | 0.92 | 0.88 |
| | LLaMA with Calibration | 0.86 | 0.86 | 0.98 | 0.92 |
| | Qwen | 0.72 | 0.76 | 0.80 | 0.78 |
| | Qwen with Calibration | 0.78 | 0.81 | 0.84 | 0.82 |
| | MobileNetV2 | 0.77 | 0.83 | 0.91 | 0.87 |
| | Vision Transformer | 0.78 | 0.49 | 0.50 | 0.49 |
| | CNN | 0.80 | 0.80 | 0.95 | 0.87 |
| | SVM | 0.77 | 0.77 | 1.00 | 0.87 |
| | Random Forest | 0.77 | 0.78 | 0.97 | 0.86 |
| | LSTM | 0.77 | 0.77 | 0.95 | 0.85 |
| | CNN-LSTM | 0.86 | 0.96 | 0.97 | 0.96 |
| Tencent | LLaMA | 0.75 | 0.80 | 0.78 | 0.79 |
| | LLaMA with Calibration | 0.82 | 0.85 | 0.88 | 0.86 |
| | Qwen | 0.70 | 0.75 | 0.74 | 0.74 |
| | Qwen with Calibration | 0.74 | 0.76 | 0.79 | 0.77 |
| | MobileNetV2 | 0.79 | 0.83 | 0.94 | 0.88 |
| | Vision Transformer | 0.79 | 0.46 | 0.47 | 0.46 |
| | CNN | 0.85 | 0.85 | 0.96 | 0.90 |
| | SVM | 0.73 | 0.73 | 1.00 | 0.84 |
| | Random Forest | 0.71 | 0.74 | 0.93 | 0.82 |
| | LSTM | 0.73 | 0.73 | 0.98 | 0.84 |
| | CNN-LSTM | 0.86 | 0.86 | 0.98 | 0.92 |
| Toyota | LLaMA | 0.81 | 0.83 | 0.86 | 0.84 |
| | LLaMA with Calibration | 0.87 | 0.90 | 0.92 | 0.91 |
| | Qwen | 0.74 | 0.77 | 0.79 | 0.78 |
| | Qwen with Calibration | 0.79 | 0.81 | 0.83 | 0.82 |
| | MobileNetV2 | 0.73 | 0.84 | 0.85 | 0.84 |
| | Vision Transformer | 0.77 | 0.49 | 0.49 | 0.49 |
| | CNN | 0.84 | 0.81 | 0.96 | 0.88 |
| | SVM | 0.74 | 0.74 | 0.97 | 0.84 |
| | Random Forest | 0.74 | 0.76 | 0.96 | 0.85 |
| | LSTM | 0.74 | 0.74 | 0.97 | 0.84 |
| | CNN-LSTM | 0.60 | 0.85 | 0.65 | 0.74 |

TABLE IV. PERFORMANCE OF MOBILENETV2 WITH DIFFERENT DATA AUGMENTATION TECHNIQUES

| Augmentation | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| No Augmentation | 0.73 | 0.84 | 0.85 | 0.84 |
| Rotation | 0.80 | 0.83 | 0.95 | 0.89 |
| Flipping | 0.73 | 0.82 | 0.87 | 0.85 |
| Zooming | 0.78 | 0.82 | 0.94 | 0.88 |
| Rotation, Flipping | 0.57 | 0.81 | 0.63 | 0.71 |
| Rotation, Flipping, Zooming | 0.77 | 0.82 | 0.92 | 0.87 |

perform better. It likely works by showing candlestick patterns at different scales, which helps with stock price prediction.

Furthermore, combining rotation and flipping result in a significant drop in performance, with accuracy plummeting to 0.57 and recall decreasing to 0.63. This suggests that these two augmentations, when used together, might introduce too much variability or noise, making it harder for the model to learn effectively. However, when rotation, flipping, and zooming are combined, the model's performance improves, achieving an accuracy of 0.77 and an F1 score of 0.87. This indicates that while combining augmentations can be risky, a balanced approach with multiple techniques can still yield positive results.

In summary, rotation augmentation alone provides the best performance, significantly improving accuracy and recall. Combining multiple augmentations can be beneficial but requires careful consideration to avoid introducing excessive noise. These findings suggest that data augmentation, when applied thoughtfully, can enhance the predictive power of models in stock price prediction.

## VI. CONCLUSION

The experimental results show that LLMs such as LLaMA and Qwen can be effective in stock price prediction using candlestick charts, especially when calibrated with techniques such as Platt Scaling. Calibration improves the accuracy and reliability of LLMs, making them more suitable for financial forecasting. Among image-based deep learning models, CNN outperforms MobileNetV2 and Vision Transformer in recall and F1 score, demonstrating its effectiveness in candlestick chart analysis. While MobileNetV2 offers computational efficiency, Vision Transformer struggles with recall. Among

models with numerical inputs, hybrid model CNN-LSTM achieves the best performance and other models such as SVM, Random Forest and LSTM achieve competitive performance. Last but not least, the impact of data augmentation techniques in model performance is also studied in this paper. The results indicate that rotation augmentation alone delivers the best performance, notably boosting accuracy and recall. Although combining multiple augmentations can be advantageous, it must be done cautiously to prevent excessive noise. These results indicate that thoughtful data augmentation can enhance model predictive power in stock price forecasting.

Future research can focus on assessing the robustness of LLMs against adversarial attacks. In practical financial applications, models may be vulnerable to minor changes in input data, such as subtle distortions in candlestick chart images, which could result in significantly different predictions. Investigating adversarial attacks on the visual components of the framework would offer deeper insights into the model's reliability and security. Implementing adversarial training could further improve the stability and robustness of the prediction system under noisy input conditions.

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# Applications of Qhali-Bot in Psychological Assistance and Promotion of Well-being: A Systematic Review

Sebastián Ramos-Cosi[1], Daniel Yupanqui-Lorenzo[2], Enrique Huamani-Uriarte[3], Meyluz Paico-Campos[4], Victor Romero-Alva[5], Claudia Marrujo-Ingunza[6], Alicia Alva-Mantari[7], Linett Velasquez-Jimenez[8]

Image Processing Research Laboratory (INTI-Lab), Universidad de Ciencias y Humanidades, Lima, Perú.[1, 3, 5, 6, 8]
E-Health Research Center, Universidad de Ciencias y Humanidades, Lima, Perú.[2, 7]
Faculty of Engineering, Universidad de Ciencias y Humanidades (UCH), Lima, Perú[4]

***Abstract*—Social robots have emerged as efficient tools in the field of psychological assistance and well-being promotion, especially known as Qhalibot in prominent areas such as mental health, education and work environments. The aim of this study is to provide a comprehensive overview of their application in these contexts, through a systematic review based on the PRISMA methodology and a bibliometric analysis. To this end, 41 articles obtained from databases such as Scopus, IEEE Xplore, Web of Science, and JSTOR were evaluated. The findings reveal that social robots offer significant benefits, such as improved adherence to therapeutic treatments, real-time emotional support, and reduced stress levels in various groups of people. These benefits have shown a positive impact on users, especially towards those facing mental health conditions or high-stress situations, improving their overall well-being. However, significant challenges were encountered, including user acceptance of these technologies, personalization of interactions to meet individual needs, and integration of these systems into pre-existing environments. Furthermore, it is identified that most of the studies have been carried out in controlled environments, which limits the transferability of the findings to real-world situations. As future lines of research, it is suggested to explore new methodologies for the implementation of these systems in uncontrolled environments, the development of innovative tools that facilitate human-robot interaction, and the evaluation of the long-term impact of these systems in diverse populations. These investigations are crucial to better understand the effectiveness and applicability of social robots in broader and less controlled contexts, which could lead to a more effective integration into daily life.**

***Keywords*—Qhalibot; robot; psychological assistance; well-being; review**

## I. Introduction

Today, mental health represents a growing global challenge [1]. The World Health Organization estimates that depression and anxiety disorders are some of the leading causes of disability globally, affecting more than 280 million people [2], [3]. Some factors such as the fast pace of life [4], high workload [5], and excessive use of technology [6] have contributed to increased stress and other psychological problems. In this context, the search for innovative solutions for psychological assistance and comprehensive well-being is crucial [7]. In the existing literature, various strategies have been explored, from cognitive-behavioral therapies [8] to mindfulness-based interventions [9]. However, access to these activities is limited due to geographical [10] and economic factors [11].

The traditional approach to mental and physical well-being has been grounded in conventional psychological therapies [12], corporate wellness programs [13], and supervised physical activities [14]. Current alternatives, such as face- to- face therapy [15] and mobile meditation [16], [17] or self-help applications [18], have shown effectiveness in reducing stress and improving quality of life. However, these strategies usually need constant human interaction, are mostly not personalized [19] and in many cases depend on the user's motivation for their continuous use.

Faced with these limitations, alternative approaches based on Artificial Intelligence (AI) [20] and robotics [21] have emerged, with the aim of offering accessible, interactive and personalized solutions. Social robots have proven to be viable tools in improving psychological well-being [22], facilitating emotional assistance and promoting healthy habits [23]. In this context, the potential of these devices in the field of mental health is highlighted, as they improve compliance with psychological therapies and promote physical activity through recreational and guided interactions [24].

Likewise, various studies have shown the positive impact of AI and robotics on mental health [25], [26], [27]. An example of this is the robots that have been used in interventions with patients with anxiety, depression and autism, achieving favorable results in the reduction of symptoms and improvement of social interaction [22]. In addition, AI platforms have proven their effectiveness in the early detection of psychological disorders through behavioral and language pattern analysis [28], [29]. These findings support the need to continue exploring technological tools in psychological assistance and well-being.

Despite the advances in this field, the existence of gaps in research on the integration of social robots in work and educational environments [30] as promoters of integral well- being is corroborated. This is because most research has focused on clinical populations or older adults, leaving aside its application in daily situations of high stress. In addition, the lack of evidence on the combination of psychological assistance

and promotion of well-being through robotics is highlighted, which justifies the performance of this systematic review.

Based on the above, this study seeks to answer the following research questions: What are the technologies used for psychological assistance and the promotion of integral well-being? What are the main challenges and opportunities in the implementation of robots in work environments to improve the quality of life of users? What are the main challenges and opportunities in the implementation of robots in educational environments to improve the quality of life of users?

The structure of the article is organized as follows: in the methodology section, the process of searching for and selecting studies for systematic review is described. Then, in the results and discussion section, the main findings on the effectiveness and applications of robots in psychological assistance and well- being are presented together with the analysis and comparison with previous literature in order to raise future implications. Finally, in the conclusions section, the key findings are synthesized and future lines of research are proposed to improve the application of these technologies in the field of well-being.

## II. Background: Definition, Concepts and Previous Applications

AI-based psychological assistance involves the use of computational systems to provide emotional support [31], guide self-care processes, and promote mental well-being [32]. In recent years, AI has proven to be an effective resource for the early detection of psychological disorders [33] and digital intervention, with applications in therapeutic chatbots [25], virtual assistants and social robots [34]. Various technologies have been used to provide emotional support and reduce symptoms of anxiety and depression [35], offering an accessible alternative to traditional therapy. In addition, in the work and educational environment, the use of technological solutions to promote well-being, such as guided active breaks, has gained importance as a preventive strategy to reduce stress [36], [37] and improve the quality of life of users.

In this context, reference is made to social robots, which are mostly used for different stages of life, an application of them are the PARO (Therapeutic Robot for Older Adults) [38] and NAO (used in education and therapy) systems [39], which have shown a positive impact on reducing stress and increasing emotional commitment in people who use them. However, allusion is made to the different ages of its consumers, as it shows a clear distinction in the use of technology.

On the other hand, psychological assistance through digital platforms has transformed the way people access emotional support [40], [41]. Tools such as Qhali-bot have enabled more accessible and effective care [42], overcoming the barriers of time and space that traditionally limited access to mental health services. These systems provide ongoing support in everyday situations of stress, anxiety, or sadness [43], providing emotional guidance in times of need [44].

AI-assisted virtual therapies have emerged as an innovative solution to complement traditional psychological care [45]. By using advanced natural language processing and machine learning algorithms, these systems provide users with immediate and personalized emotional support. This approach has proven especially useful in situations where access to therapists is restricted or in times of crisis, ensuring that individuals can get the support they require in a timely manner.

## III. Gaps in the Literature

Despite advances in research on social robots and their implementation in psychological assistance, there are limitations in the existing literature. One of the main constraints is the lack of longitudinal studies examining the long-term effects of robot use on mental well-being and adherence to therapies. In addition, numerous studies have been conducted with small samples or in highly controlled environments, making it difficult to generalize the results to diverse and representative situations of the general population. Likewise, a geographical bias in scientific production has been identified, with a greater concentration of studies in countries with advanced access to technology [54], [55], excluding countries with more limited technological infrastructure and resources [56].

In this sense, a deeper exploration of the integration of robots in work and educational contexts [73], [77] is required, addressing ethical and sociocultural aspects that influence their acceptance and effectiveness. Therefore, it is necessary to broaden the research focus towards the interaction between humans and robots in dynamic environments [69], [70], where the adaptability of these technologies is evaluated in real situations. Likewise, it is recommended to carry out comparative studies between different robotic platforms to identify the specific characteristics that contribute to a better response in psychological assistance and well-being. In this context, these lines of research will improve the current understanding of the impact of robots on mental health and optimize a design and application to maximize their benefits in the various areas.

## IV. Materials and Methods

While interest in AI in healthcare is on the rise, studies on the impact of holistic wellness robots on psychological support and wellness promotion remain limited. Most research focuses on mental health chatbots or social robots for specific populations, such as children with autism or older adults. However, there is a gap in the literature on the integration of psychological assistance and active breaks in work and educational settings using robotics and AI, which highlights the need for a systematic review that synthesizes and evaluates the existing findings.

To address this gap in research, a systematic review based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol has been chosen. This approach ensures transparency and rigor in the collection, selection and analysis of existing scientific literature [46]. To do this, multiple indexed databases will be searched, using bibliometric tools to analyze trends and relationships between studies. The use of PRISMA in systematic reviews has been established as an effective methodological strategy to minimize bias and improve the replicability of findings. PRISMA has been widely used in studies on technological interventions in mental health, demonstrating its validity in the identification

and evaluation of relevant literature. In addition, compared to other methodologies such as narrative reviews or scoping reviews, PRISMA allows a more detailed analysis on the quality and relevance of the selected studies, which guarantees the robustness of the synthesis of the information.

### *A. Review Approach*

High-impact scientific databases such as Scopus, IEEE Xplore, Web of Science and JSTOR will be searched, with the aim of ensuring broad and multidisciplinary coverage. In addition, bibliometric analysis tools such as VOSviewer and Bibliometrix will be used to identify trends in the literature, collaborative networks and thematic clusters within the framework of AI research applied to mental health and well- being. The selection of these databases is based on their recognition within the scientific community and their indexing of peer-reviewed articles in technology, psychology, and health. SCOPUS provides a global perspective on the impact of research at a global level [47], while IEEE Xplore allows for a more technical approach to the implementation of AI and robotics in health. On the other hand, Web of Science and JSTOR expand the scope to Social Sciences and applications in educational and work environments [48].

The keyword group used to check the title, abstract, and keywords of articles collected in the Scopus database: ( TITLE-ABS-KEY ( robot ) OR TITLE-ABS-KEY ( virtual AND assistant ) AND TITLE-ABS-KEY ( mental AND health ) OR TITLE-ABS-KEY ( psychological AND assistance ) OR TITLE-ABS-KEY ( therapy ) OR TITLE-ABS-KEY ( counseling ) OR TITLE-ABS-KEY ( psychology ) AND TITLE-ABS-KEY ( well-being ) OR TITLE-ABS-KEY ( emotional AND support ) )

The keyword group used to check the title, abstract, and keywords of articles collected in the IEEE Xplore database: ("Document Title":robot) AND ("Abstract":virtual) AND ("Abstract":assistant) AND ("Abstract":mental) AND ("Abstract":health) AND ("Abstract":p sychological) AND ("Abstract":well-being) OR ("Abstract":emotional) AND ("Abstract":support)

The keyword group used to check the title, abstract, and keywords of articles collected in the Web of Science database: ((TI= ("robot" AND "virtual" AND "assistant" AND ("mental" AND "health" OR "psychological" AND "assistance"))) OR (AB= ("robot" AND "virtual" AND "assistant" AND ("mental" AND "health" OR "psychological" AND "assistance"))) OR (AK= ("robot" AND "virtual" AND "assistant" AND ("mental" AND "health" OR "psychological" AND "assistance"))))

The keyword group used to check the title, abstract, and keywords of the articles collected in the JSTOR database: ((((((ti:"robot") AND (ab:"virtual")) AND (ab:"assistant")) AND (ab:"mental")) AND (ab:"health")) OR (ab:"psychological")) AND (ab:assistance)

Fig. 1 shows a flowchart that describes the various stages of the information selection process. The initial search yielded 454 Scopus publications, 132 IEEE Xplore publications, 359 Web of Science publications, and 120 JSTOR publications, making a total of 1,065 documents across all databases. In addition, a filtering by thematic area was carried out, which favored the inclusion of studies related to the analyzed topic. Next, the search criteria were limited to journal articles and systematic reviews. This is because journal articles are peer- reviewed and have greater support than other types of research. Likewise, the inclusion of the systematic reviews included in this analysis corresponds to the importance of their scope and information provided [49]. For this reason, other types of documents such as conference papers, book or patent chapters, editorial notes, letters and surveys were discarded, since they contribute very little to the results in the direction of this topic. The selected items do not have a time specification. After the search filter based on predefined inclusion and exclusion criteria, the number of relevant papers was 61 articles in Scopus, 90 articles in IEEE Xplore, 82 articles in Web of Science, and 44 articles in JSTOR. Subsequently, the titles and abstracts of each document obtained were examined to determine their relevance in the scope of this study. Finally, with a distribution of 27 from Scopus, 4 from IEEE Xplore, 7 from Web of Science and 3 from JSTOR; screening of titles and abstracts of these studies resulted in a total of 41 papers. The next stage of filtering involved using Mendeley, a reference manager, to remove duplicate articles. It was found that there were no duplicate documents and in such a case, the 41 relevant documents were retained for the in-depth review.

The selected databases allowed access to high-impact literature in different areas of knowledge. Likewise, the use of different databases was largely relevant for this study, since it allowed obtaining articles collected from different databases, not limiting themselves to a single one, nor following only one line of research. This is because SCOPUS provides citation metrics and impact analysis [47], while IEEE Xplore specializes in technology and computing. Web of Science expands access to emerging literature [48] and JSTOR offers psychology and social science studies. On the other hand, for bibliometric analysis, VOSviewer is used for the visualization of co-occurrence networks in keywords, co-authorship and collaboration by countries, while Bibliometrix will allow the quantitative analysis of trends and patterns in the reviewed literature.

As a result, a systematic review in this field is essential due to the diversity of research in multiple disciplines such as psychology, technology, and health sciences. The application of PRISMA will ensure a thorough analysis of the literature, allowing the identification of patterns, trends and gaps in research on the use of AI and robotics in psychological assistance and the promotion of well-being. This synthesis will contribute to the design of future research and the development of more effective and accessible technological solutions for stress management and mental health.

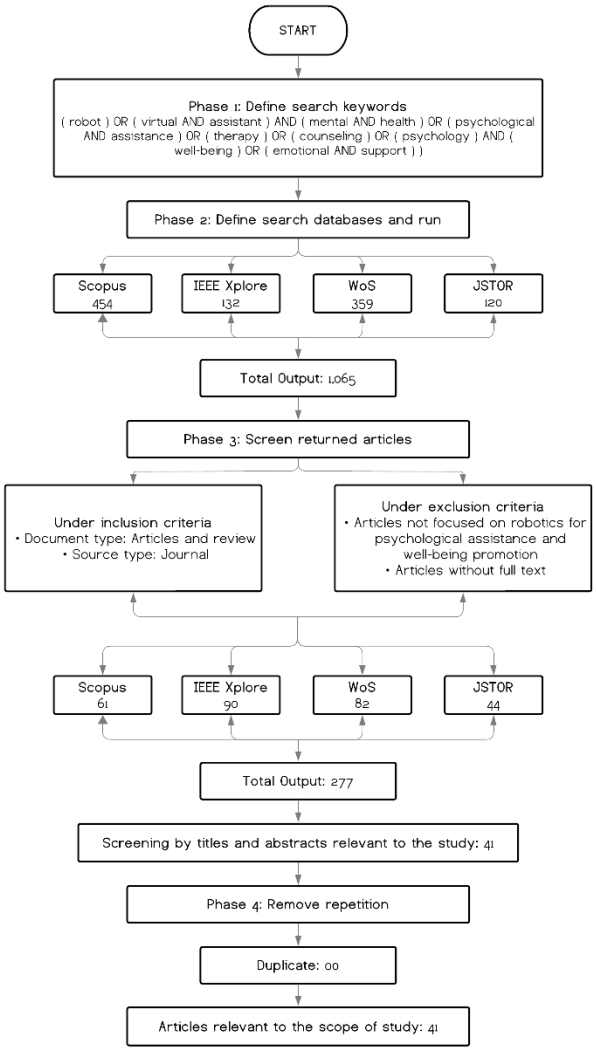


Fig. 1. PRISMA-based flowchart.

### B. Analysis

The initial phase of the analysis consisted of the observation of the bibliometric data obtained from the selected databases. The frequency of publication of articles according to the year, the geographical location of the studies, the journals in which they were published and the research methods used were analyzed. Early findings suggest an increase in scientific output related to AI applied to mental health. The publications focus mainly on technology and psychology journals. Geographically, the studies come mainly from countries with a high development in AI and digital health, such as the United States and China. In terms of methodology, empirical studies based on controlled experiments and systematic reviews predominate, with a growing number of studies integrating biometric data analysis into well-being interventions.

To ensure a rigorous analysis of the included articles, the methodological approaches used in the literature were contrasted with the findings of this systematic review. Studies focused on chatbots [25] for mental health, digital therapies [45] and social robots [22], [23] were identified, highlighting the use of natural language processing techniques and biofeedback as main intervention strategies. Existing literature has explored approaches such as AI-assisted cognitive behavioral therapy [8], gamification in active breaks, and the use of biometric sensors to measure stress, supporting the rationale for the study. However, a lack of research combining psychological assistance and promotion of physical well-being through robotics was detected, which positions this systematic review as a key contribution to identify opportunities and gaps in the integration of these technological approaches in work and educational environments.

## V. Results and Discussion

Bibliometric analysis of records obtained from Scopus, IEEE Xplore, Web of Science, and JSTOR facilitated the identification of key trends in AI research applied to psychological assistance and well-being. We examined the frequency of publications per year, the geographical distribution of studies, the most commonly used keywords and co-authorship networks between researchers. The results show an increase in scientific production in this field, with a significant peak in recent years. The United States and China stand out as the main contributors to the literature, and the most recurrent words include "robotics," "human," and "social robots." The analyses of co-authorship and international collaboration show consolidated research networks, with specific clusters of collaboration. This bibliometric analysis is considered an essential tool in systematic tools, as it allows evaluating the evolution of an area of study, identifying gaps in the literature and understanding the dynamics of scientific production, in order to provide an empirical basis for future research and technological developments in the area of well- being.

### A. Bibliometric Analysis

Bibliometric analysis is a quantitative method that analyzes scientific production through indicators such as publications, citations, and collaboration networks, revealing trends and evaluating the impact of disciplines in the academic literature. To perform these analyses, specialized tools such as VOSviewer, Bibliometrix, CiteSpace and Gephi are used, which simplify the visualization of co-authorship networks, the co-occurrence of keywords and international collaboration. In the framework of this study, VOSviewer was used to visualize the relationships between keywords and authors [50], and Bibliometrix, implemented in R, to process large volumes of data and identify trends and citation patterns in the literature [51]. These tools make it possible to acquire a structured vision of the evolution of knowledge in a specific area, facilitating informed decision-making and strategic organization in information.

*1) Keyword co-occurrence map*: A keyword co-occurrence map is a graphical representation that shows the connections [52] and frequency with which some terms are found in the scientific literature, such as the titles, abstracts, and keywords of articles obtained from databases such as Scopus, IEEE Xplore, Web of Science, and JSTOR. These maps, created using clustering algorithms, facilitate the identification of the central themes of a field of study [50], and in turn, allow us to

understand the evolution and interconnection of concepts over time. This co-occurrence analysis is relevant in bibliometric reviews, especially in areas such as AI in health, where it helps to identify booming trends and gaps in research. In addition, this approach makes it easier to track the evolution of specific terms, as it highlights their growing relevance in fields such as digital psychology.

With the use of VOSviewer and a minimum of 3 keyword co-occurrences; 357 keywords co-occurred, and 3 significant clusters were identified. Fig. 2 shows a network visualization map of the 3 groups of co-occurring keywords with 27 elements, 166 links, and a total link strength of 298. The keywords that have the highest number of links are understood to be the most impactful and remarkable. The keywords with clearly larger nodes than the rest are "social robots", "robotics", "human" and "psychology". The size of a keyword shows the number of times it has been mentioned as an author keyword in research papers, while keywords close to it show its co- occurrence in research papers. Clusters are represented by colors and are indicators of keywords most often. In this case, the keywords "social robots", "well being", "human robot interaction", "mental health" and "socially assistive robots" are represented by the color red, which indicates that they are terms that co-occur frequently. This information can guide researchers when choosing the appropriate keywords in their papers, as it ensures more effective indexing and retrieval of research.

This bibliometric analysis shows that the study focuses on the development and use of robotic technology to enhance people's quality of life and mental health, in turn, it explores the complexity of the interaction between humans and robots in the recognition of emotions. The connection and size of the nodes in the analyses suggest an important interconnection between human-robot interaction, emotion recognition and quality of life, underscoring the relevance of a comprehensive approach in this emerging area.

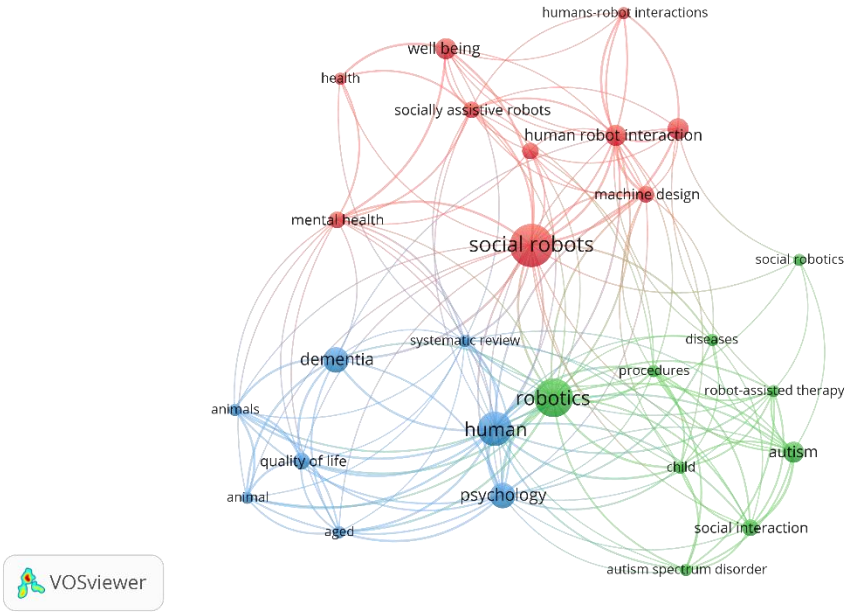


Fig. 2. Keyword co-occurrence map in VOSviewer.

*2) International co-authorship map*: Co-authorship analysis facilitates the identification of collaboration networks between researchers, revealing the structure of scientific production in an area of study [53]. This approach allows us to understand the formation of research communities and identify the influence of authors in the area.

The minimum number of documents identified in VOSviewer per author was set at 1 to filter the maximum co- authorship range, and in turn, analyze possible improvements in that aspect. This generated 189 authors, including the lead author and his co-authors. The largest set of connected articles was 13 documents. These connected elements generated 39 clusters and 499 links. The visualization co-authorship network in Fig. 3 shows researchers Aymerich- Franch L. and Moshayedi, A. J. as the most frequent collaborations. This co-authorship network represents an improvement in the collaborative capacities of a network of researchers at an international level, which means a great advance in the different areas.

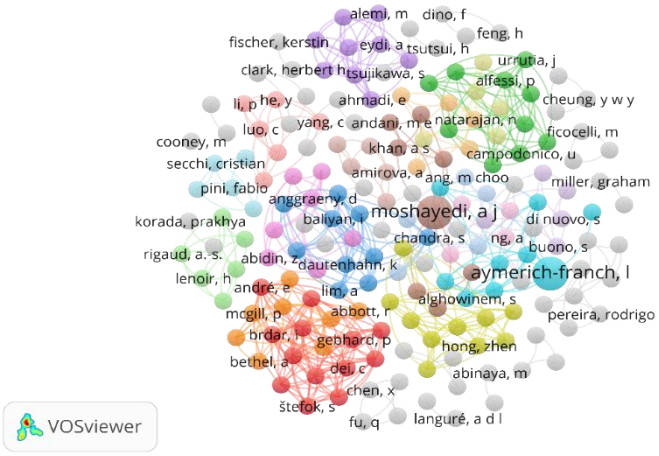


Fig. 3. Co-authoring map in VOSviewer.

*3) Country collaboration map*: The analysis of collaboration between countries facilitates the identification of scientific production at the global level, showing the leading countries in research in that field, and in turn, shows their minor representation of the subject.

Using the VOSviewer tool, the number of documents from a country was set at 3 documents, in order to maximize country analysis for further sustained identification. The number of countries detected by the VOSviewer software was 40 countries, of which 10 met the established criteria. Fig. 4 shows the countries active in research on robots for psychological assistance and promotion of well-being. These connected elements resulted in 5 clusters, 12 links, and a total bond strength of 15. As can be seen, the largest nodes represent China, the United States, the United Kingdom, and Italy. This indicates that researchers from these countries have contributed the most to studies on robotics in the application of psychological assistance and promotion of well-being.

These results are consistent with studies that have shown a geographical concentration of scientific production in countries with higher levels of investment in technology and innovation [54]. It found that nations in North America, Western Europe, and East Asia are leading the adoption of developing technologies [55], while places like Africa and Latin America face significant challenges due to limitations in infrastructure and financing [56].

On the other hand, research in countries such as China has been shown to be instrumental in the implementation of robotics in psychological care [57], with innovative approaches combining AI and robotic-assisted therapy [58]. However, the low representation of other countries in collaboration maps indicates the need to promote international collaboration and strengthen equitable access to these developments [59].

In summary, the strong concentration of research power in a few countries highlights the importance of promoting international cooperation projects [60] that facilitate the reduction of inequalities in access to technology and knowledge. Identifying these inequalities can guide funding policies and collaborative strategies that promote more equitable [61] and globally representative research on the use of robotics for psychological assistance and well-being.

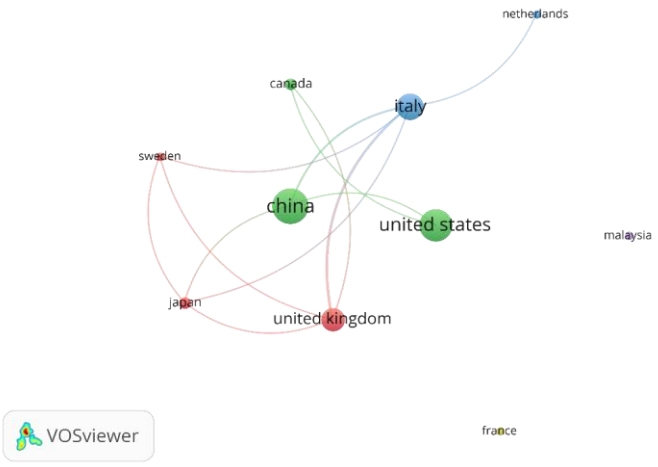


Fig. 4. Country co-occurrence map in VOSviewer.

*4) Distribution of publications by year*: The analysis of the distribution of publications over time allows us to identify trends and crucial moments in the evolution of an area of study.

Fig. 5 shows the number of articles published on the subject of robots for psychological assistance and promotion of well-being. It is observed that the number of articles published in 2015 was only one, which represents a minimum of interest in this type of topic. It is also observed that in the range from 2021 to 2023 there was a growth in terms of relevant investigations, with an average of 6. However, there is a boom in papers in 2024, with 10 publications, indicating an expected interest in this area, as emerging technologies are aligned with robotics and AI in conjunction with research.

This trend could be linked to the rapid advancement of smart technologies and their application in the mental health and wellness sector [62], [63]. In particular, the introduction of new AI-based tools has generated greater interest in the scientific community [64], as it represents efficient novelties in their daily lives, which drives their growth in this area. In addition, the boom shown in 2024 indicates greater investment in research and development, promoted by academic institutions or international organizations that aspire to strengthen the integration of robotics in psychological care.

On the other hand, the evolution of the number of publications over time reflects the impact of external factors, such as the COVID-19 pandemic, which accelerated the digitization of health services [65] and impacted the acceleration of the search for technological solutions for emotional well-being [66]. As the scientific community continues to explore the applications of robotics in this field, it is likely that the trend of publications will continue to grow, highlighting the need to generate interdisciplinary collaborations and supporting policies that facilitate the development and implementation of these technologies at a global level.

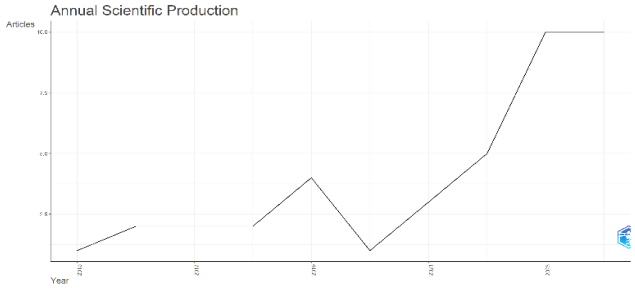


Fig. 5. Distribution of publications by year.

*5) Distribution of publications by journals*: The analysis of the distribution of publications by journals allows us to understand the disciplines that contribute to an area of research and their predominant approaches.

Fig. 6 shows the distribution of the articles included in the analysis by journal titles. It can be seen that the leaders in journaling in this area are Frontiers In Robotics And AI and IEEE Access with a total of four publications each, followed by ACM Transactions on Human-Robot Interaction, International Journal of Social Robotics and Journal Of Autism And Developmental Disorders with two publications each. The remaining journals in the analysis show one article each.

This analysis highlights the importance of certain journals in the dissemination of knowledge about robotics applied to psychological care. The journals with the largest number of publications have contributed significantly to the progress of the field, offering platforms for the exploration of new methodologies and technological applications. This pattern indicates that interest in robotics for psychological care is mainly driven by disciplines such as AI [67], [26], human-robot interaction [68], and mental health [27], which find in these journals an appropriate channel to disseminate their findings. In addition, the diversity of journals in the analysis reflects the interdisciplinary nature of this field of study, which points to the importance of cooperation between specialists from different areas to enhance future research and practical applications.

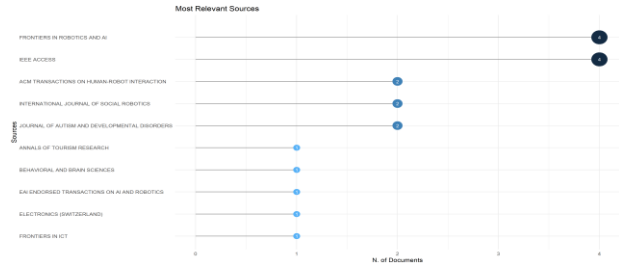


Fig. 6. Distribution of articles published by journal titles.

## B. Content Review

The final analysis included 41 documents selected using the PRISMA methodology, covering studies on the use of social robots in psychological assistance and integral well-being. The selection focused on publications that investigated the technologies used, implementation in work and educational environments, as well as the associated challenges and opportunities. The thematic distribution reflected a predominance of research in computational psychology, AI applied to health, and social robotics, which allowed for a focused view of the problem. This approach allowed the review to be organized around three main questions, each in a well-founded manner.

- What are the technologies used for psychological assistance and the promotion of integral well-being?
- What are the main challenges and opportunities in the implementation of robots in work environments to improve the quality of life of users?
- What are the main challenges and opportunities in the implementation of robots in educational environments to improve the quality of life of users?

The above points focus on the design of a content review structure illustrated in Fig. 7 to guide a detailed, deductive, and systematic review of each document. This approach was explored in subsections, which offer a comprehensive overview of the state of robotics in psychological assistance and well-being promotion, related challenges, research gaps, and directions for future research.

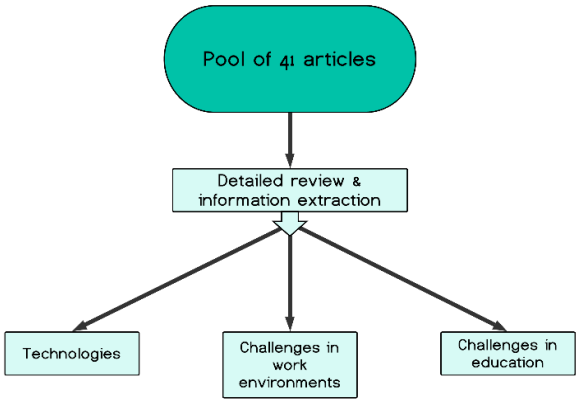


Fig. 7. Structure of the systematic content review.

*1) Technologies used*: Fig. 8 shows the distribution of 23 articles on technologies. This analysis of the filters obtained suggests a growing interest in the design of robots with social capabilities. Human-robot interaction highlights the importance of optimizing these interactions to improve the functionality and acceptance of the technology [69], [70]. On the other hand, the lower number of publications on robotic assistants in an applied way suggests that even in this area, although relevant, it is less explored, suggesting an opportunity for future research. Given this, it is considered necessary to promote interdisciplinary collaboration to ensure accessibility worldwide [71], in order to elevate advances in social robotics and turn them into adoption tools in psychological assistance and well-being. Taken together, these findings indicate that social robotics is expanding [72] and the multidisciplinary approach is essential to advance the integration of everyday life technologies.

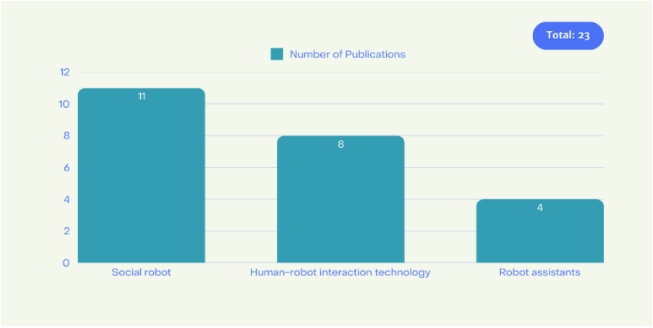


Fig. 8. Distribution of articles by technologies.

*2) Challenges and opportunities in the implementation of robots in work environments*: Deploying robots in work environments presents both challenges and opportunities [73]. One of the most significant challenges is the adaptation of workers to the integration of these systems [74], as resistance to change and the perception that robots could replace jobs in some industries have been identified [75]. However, automation and the use of robots in the workplace also offer multiple opportunities, such as improving worker safety by reducing exposure to hazardous environments and optimizing repetitive tasks to increase operational efficiency.

Fig. 9 shows an analysis indicating that robots in personal healthcare have proven to be particularly relevant in the care of patients with reduced mobility or chronic diseases, facilitating continuous monitoring of vital signs and providing support in daily activities. On the other hand, mental wellbeing coaches have been investigated as psychological support tools, offering AI-based therapies that have been shown to be effective in reducing stress and anxiety.

In interaction in industrial environments, robots have been used to increase safety in high-risk tasks, such as handling hazardous materials or working in extreme conditions [76]. Despite these advantages, there is still a need to address ethical and regulatory aspects in the application of these technologies, in order to ensure that their adoption is equitable and does not cause inequalities in access to automated tools in different work sectors. In this sense, the growth in research on robots in work environments shows a continuous interest in their ability to transform different industries. However, the effective implementation of these technologies requires a balanced approach that considers challenges and associated benefits, with the aim of promoting technological development that improves the quality of work and ensures the ethical and sustainable integration of robots in the workplace.


Fig. 9. Distribution of items by challenges in work environments.

*3) Challenges and opportunities in the implementation of robots in educational environments*: The use of robots in educational contexts presents challenges and opportunities that suggest that they should be addressed quickly [77], given the importance of education in the global aspect. In this sense, one of the main challenges is the acceptance of these technologies in the school and university environment, since their implementation requires a process of adaptation for both teachers [78] and students [79]. Fig. 10 shows an analysis in which robots have proven to be valuable tools in various areas, including improving the health and well-being of students, supporting the early identification of mental disorders, and promoting emotional health.

In the health and wellbeing sector, robots have been used as assistants in teaching strategies to cope with stress and anxiety [34], providing support to students in periods of high academic

load. Likewise, the identification of mental disorders using AI- equipped robots has made it possible to identify patterns of behavior linked to disorders such as depression and anxiety [28], [29], which promotes early and timely interventions.

In the area of emotional health, robots have been used in educational contexts as facilitators of social interaction [22], particularly in students with communication problems. In addition, it has been identified that these devices can generate a positive impact on the emotional management of students and promote the acquisition of social skills for their integral development. While the integration of robots into educational environments offers numerous benefits, challenges remain to be addressed in terms of user accessibility from a psychological perspective, ethical considerations regarding data use, and student data privacy. Accordingly, research in this field continues to advance, so it is essential to ensure an inclusive approach that maximizes the potential of these technologies for the well-being and education of future generations.

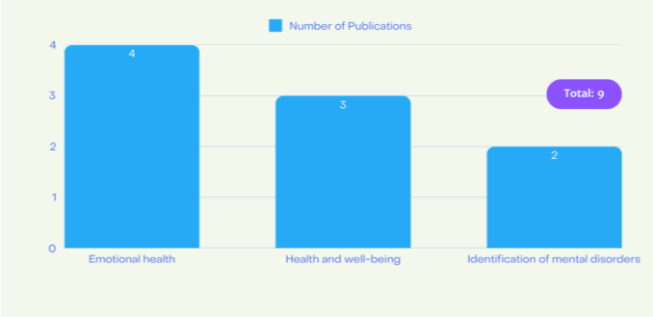


Fig. 10. Distribution of articles by challenges in educational settings.

## VI. Conclusion

This study's analysis revealed a steady increase in the number of publications on the topic since 2020, indicating growing interest and considerable investment in research related to robotics and AI in the context of mental health, driven by technological advances and the need for innovative solutions in a critical field such as psychological well-being.

The studies analyzed identified the United States and China as the main contributors to this literature, showing a geographic concentration that highlights inequalities in scientific production. The review also notes that the most frequently used keywords were "robotics," "human," and "social robots," reflecting the central themes prevailing in current studies and offering guidance for future research. Furthermore, the collaboration between authors such as Aymerich-Franch L. and Moshayedi A. J. points to a strengthening of the collective dynamic, essential for the advancement of knowledge. This collaborative approach is essential to addressing the ethical and practical challenges associated with the implementation of robotic technologies in workplace and educational settings.

These results indicate that, while significant progress has been made, there are still underexplored areas that require attention, such as the design of robots with more advanced social capabilities and their effective integration into work and educational settings. In this sense, this bibliometric analysis provides a structured perspective on the evolution of knowledge in the field of AI applied to psychological assistance and establishes a framework for future research.

Finally, it is crucial to continue researching the ethical and practical implications of the use of these technologies, ensuring that their development is carried out in an inclusive and equitable manner. As we move towards a future where robotics and AI play a greater role in our daily lives, it is crucial to promote interdisciplinary collaborations that strengthen the positive impact of these innovations on human well-being.

## VII. Considerations for Future Research

- Consider comparing the effectiveness of different types of robots and AI technologies in various environments and populations.
- Investigate the efficiency of different interaction modalities, such as virtual exposure therapy or social skills training tailored to each person's specific needs.
- To develop innovative tools to assess the performance and acceptance of robots in psychological care.
- Evaluate the impact of AI-based robots compared to traditional methods, such as therapies or self-help apps.
- Explore the integration of technologies such as Augmented Reality and biometric feedback to improve human-robot interaction.
- Investigate factors that contribute to acceptance and trust in robots, as therapists, the potential risks and ethical challenges associated with their use.

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# Level of Anxiety and Knowledge About Breastfeeding in First-Time Mothers with Children Under Six Months

Frank Valverde-De La Cruz[1], Maria Valverde-Ccerhuayo[2], Ana Huamani-Huaracca[3], Gina León-Untiveros[4], Sebastián Ramos-Cosi[5], Alicia Alva-Mantari[6]*

Programa De Estudios De Enfermería, Universidad De Ciencias y Humanidades, Lima, Peru[1, 2]
E-Health Research Center, Faculty of Health Sciences, Universidad De Ciencias y Humanidades, Lima, Peru[3]
Universidad Peruana Del Centro, Huancayo, Peru[4]
Image Processing Research Laboratory (INTI-Lab), Universidad De Ciencias Y Humanidades, Lima, Peru[5, 6]

***Abstract*—The World Health Organization notes that one in five women of reproductive age faces episodes of anxiety. In Latin America, more than 50% of women experience postnatal anxiety, and in Peru, in Huánuco, 40% of first-time mothers have moderate anxiety. The aim of this study is to analyze the relationship between the level of anxiety and knowledge about breastfeeding in first-time mothers with children under six months of age. The study has a correlational quantitative approach, in which STAI questionnaires and the Breastfeeding Knowledge Instrument were applied to a total of 166 mothers, using SPSS and the multinomial logistic regression model. The results indicate that 57.23% of the mothers are young, 53.01% have completed secondary school, 22.89% study, and 63.25% had a normal delivery, with 41.57% experiencing complications. In addition, 56.16% of the children were between 4 and 5 months old. Also, 24.10% of mothers with moderate state anxiety and medium knowledge about breastfeeding and 22.29% with moderate trait anxiety. It was found that complications during childbirth (p=0.026, OR=1.025753) and the mother's occupation (p=0.013, OR=1.149548) are significantly related to anxiety. It is concluded that, although anxiety does not directly affect knowledge about breastfeeding, it is crucial to offer specific psychological and educational support for new mothers, particularly addressing sociodemographic factors.**

***Keywords*—Anxiety; knowledge; breastfeeding; first-time mothers; children**

## I. Introduction

The World Health Organization (WHO) indicates that one in five women of reproductive age faces episodes of anxiety, which, if not treated in a timely manner, can evolve into depressive symptoms in 13% of mothers during the postpartum period [1], [2]. Likewise, the Communication Organ of the General Council of Official Colleges of Psychologists (INFOCOP) reports that more than 30% of women who have given birth do not receive postnatal counseling in the first days, a critical period in which the lack of support can trigger significant psychological alterations [3].

Emotional disorders and anxiety during the perinatal period are a global challenge for mental health [4]. In Serbia, about 40% of women who experience their first birth develop postpartum anxiety, evidencing the vulnerability associated with this stage [5]. Similarly, in Spain, motherhood has been reported to have a significant impact on psychological well- being, with 61% of first-time mothers manifesting symptoms of moderate anxiety [6]. These data highlight the urgent need to strengthen psychological support during this critical period to protect maternal mental health.

In Latin America, more than 50% of women experience postnatal anxiety, and 37.1% of them develop symptoms of depression, evidencing the high prevalence of this problem in the process of adaptation to the maternal role [7]. These figures highlight that postnatal anxiety is one of the most significant challenges in maternal mental health. Studies underscore the importance of prioritizing psychological care during this stage, as emotional disorders not only affect mothers' well-being, but also negatively impact the family environment and the development of healthy bonds [8].

In Peru, anxiety is recognized as a common emotional response in first-time mothers, linked to factors such as alterations in sleep patterns and an unbalanced diet [9]. In Huánuco, 40% of first-time mothers have moderate anxiety, while in Cusco this figure rises to 63.3% in women with premature newborns [10]. These figures reflect the importance of addressing maternal mental health, considering regional differences and specific factors that increase vulnerability at this critical stage, in order to prevent negative impacts on both the mother and her environment.

Anxiety is an emotional response characterized by intense feelings of fear and worry in the face of situations perceived as threatening [11]. It is classified into two main types: state anxiety, which is transitory and occurs as a reaction to specific stimuli, generating tension or restlessness that disappears once the triggering factor is eliminated; and trait anxiety, which is a persistent characteristic of personality [12]. The latter predisposes to perceive a wide range of situations as threatening, even if they do not represent a real danger, increasing the frequency and intensity of episodes of state anxiety.

Symptoms of anxiety include difficulty making decisions, tension, general malaise, sleep disturbances, fear, and even nausea [13]. These manifestations are usually associated with

factors such as physical overload, nervous system alterations, chronic diseases and substance use [14]. In women facing motherhood for the first time, the diagnosis is made through a detailed clinical interview. This process assesses the specific symptoms of anxiety, its duration, and the impact on daily life, such as the ability to provide breast milk and adequately attend to the needs of the newborn [15].

On the other hand, mothers face the responsibility of promoting breastfeeding, considered a fundamental pillar in the nutrition of newborns. However, the United Nations Children's Fund (UNICEF) reports that 50% of newborns do not receive breast milk during the first hour of life [16]. This delay not only affects the baby's initial nutrition, but also delays the establishment of maternal bonding, a crucial aspect that is strengthened through the act of breastfeeding, with important benefits for both mother and newborn [17].

The ability to provide breast milk depends both on physiological factors, which determine adequate milk production and transfer, and on psychological aspects and the level of maternal knowledge about optimal breastfeeding practices [18]. These include correct breastfeeding techniques and understanding the appropriate periods for feeding the baby [19]. In Mexico, 69% of postpartum women have intermediate knowledge about breastfeeding, although only 30% know the concept of a lactation [20]. In Colombia, 27% of first-time mothers have deficient knowledge about breastfeeding, evidencing the need to strengthen education in this area [21].

In Lima, 80.4% of first-time mothers have intermediate knowledge about breastfeeding, although they have inconsistencies in certain definitions, influenced by factors such as incomplete educational level and early maternal age [22]. However, this problem intensifies in regions such as Tumbes, where the Demographic and Family Health Survey (ENDES) revealed that only 46.8% of mothers support breastfeeding [23]. This situation compromises children's health, by restricting access to an essential food for growth and development, increasing the risk of nutritional deficiencies and diseases in early stages of life.

The WHO defines breastfeeding as an essential and irreplaceable process to provide infants with the nutrients necessary for optimal development [24]. In addition to strengthening the immune system and reducing the risk of disease in the baby, it offers benefits to the mother, favoring her postpartum recovery and decreasing the incidence of long-term conditions [25]. Exclusive breastfeeding is recommended for the first six months of life, followed by adequate complementary feeding. Nutritional deficiency at this critical stage can increase vulnerability to disease, malnutrition, and chronic conditions [26], [19].

Studies on breastfeeding anxiety and knowledge present significant gaps that justify the need for complementary research, especially in the educational field. Furthermore, it is crucial to conduct studies that consider contextual variables, such as family support and birth complications. This highlights the importance of an integrative approach that analyzes how maternal breastfeeding knowledge, anxiety levels, and sociodemographic conditions interact to influence maternal and child well-being.

The aforementioned factors show the importance of assessing the relationship between the level of anxiety and knowledge about breastfeeding in a specific context. Based on this, it is hypothesized that anxiety in first-time mothers significantly influences their knowledge about breastfeeding, affecting their ability to assume this essential responsibility. This condition could hinder the acquisition and retention of key information about breastfeeding, compromising its proper implementation. In this sense, the present study aims to analyze the relationship between the level of anxiety and knowledge about breastfeeding in first-time mothers with children under six months.

## II. Related Works

Gancedo, et al. [27] conducted a study to analyze the factors associated with the level of anxiety and knowledge about childcare and breastfeeding in first-time pregnant women, exploring the related clinical and demographic variables. They used a cross-sectional quantitative design with the Trait State Anxiety Inventory (STAI) questionnaire complemented with questions on sociodemographic data, childcare and breastfeeding in a sample of 104 pregnant women. The results showed that the average age was 34.2 years, 23.1% had a psychopathological history, 61.5% were university students, 17.3% smoked during pregnancy and 88.4% planned to breastfeed. The mean STAI was 18.1, being significantly higher in pregnant women who smoked and had a history of psychopathology. In addition, the relationship between knowledge and anxious profile was linked to being a foreigner and a university student. The authors concluded that pregnant women who smoked, had a history of psychopathology, or did not plan to breastfeed had greater anxiety.

Prieto, et al [28] conducted research with the aim of analyzing the relationship between gestational anxiety, psychological development, and reactivity of the hypothalamic- pituitary-adrenal (HPA) axis in infants aged 2 to 3 months. To do this, they carried out a longitudinal quantitative study with the participation of 141 first-time mothers in their third trimester of gestation, to whom the State-Trait Anxiety Inventory (STAI) was applied, consisting of 40 questions on different aspects of anxiety. In addition, saliva samples were taken from the infants to measure cortisol levels as a marker of stress. The results showed that the average age of the pregnant women was 32.9 years and that mothers with prenatal anxiety had a positive correlation with other psychopathological symptoms, such as interpersonal sensitivity and obsessive- compulsive syndrome. The authors underscored the need to continue exploring this field to develop effective psychological interventions that protect mental health during pregnancy.

Ali [29] in his systematic review, examined the experiences of women with postpartum anxiety disorders, including generalized anxiety disorder (GAD), panic disorder (PD), obsessive-compulsive disorder (OCD), and post-traumatic stress disorder (PTSD). The study used a quantitative methodology and collected information from recognized databases such as MEDLINE and PsycINFO. Of the 44 articles selected, the results indicated that most women suffered from more than one anxiety disorder, frequently associated with

postpartum depression. In addition, these disorders were shown to have negative effects on child upbringing and development. The authors stressed that research in this area remains limited, which prevents definitive conclusions from being drawn. They underscored the need for further studies to broaden understanding of this topic and generate effective interventions that mitigate the impact of postpartum anxiety disorders on mothers and their children.

Álvarez, et al [22] conducted a study whose objective was to determine the level of knowledge about breastfeeding in first-time mothers. This study, with a quantitative and cross-, sectional approach, used a questionnaire validated by the authors, applied to 276 first-time mothers. The results showed that 80.4% of the participants had regular knowledge about breastfeeding, while 47.82% of the mothers under 23 years of age had deficient knowledge. In addition, it was observed that 73.91% of the mothers with low knowledge were from the provinces, establishing a positive correlation between the mother's origin and her level of knowledge. The authors concluded that, although knowledge about breastfeeding is predominantly average, this does not guarantee its adequate application in practice. Therefore, they highlighted the importance of conducting additional research to better understand this problem and design more effective educational strategies to improve the practice of breastfeeding.

Nath, et al [30] analyzed the relationship between prenatal maternal anxiety disorders and the quality of the mother-child bond in the postpartum period. They used a longitudinal design with structured clinical interviews with 454 pregnant women, following them during pregnancy and after delivery. The Edinburgh Postnatal Depression Scale was applied at the beginning and middle of pregnancy, and after childbirth the Postpartum Linkage Questionnaire was used. In addition, mother-child interaction was assessed in 204 mothers through video recordings. The results indicated that gestational anxiety was significantly associated with a negative perception of the mother-child bond, although this association was not observed in the recorded interactions. The authors concluded that maternal anxiety disorders should be addressed before or during gestation to prevent problems that could affect the well-being of both mother and child in the postpartum period.

## III. Materials and Methods

### A. Research Approach and Design

The present study is quantitative in which numerical resources are used, with a descriptive approach based on the variables, cross-sectional because a single intervention is carried out and correlational to determine the relationship between the level of anxiety and knowledge about breastfeeding in first-time mothers with children under six months. This approach allows for data collection and analysis, facilitating a deep understanding of trends related to both variables [31], [32].

### B. Population, Sample and Sampling

The study population is made up of first-time mothers with children under six months of age, registered at the National Maternal Perinatal Institute, the Laura Rodríguez Dulanto Duksil Maternal and Child Center and the Luis Felipe De Las Casas Health Center, located in Lima. From the data collected in visits to these institutions, a total population of 389 first-time mothers were identified.

To determine the sample, the statistical software EPIDAT 4.2 [33] was used, applying a confidence level of 95%, an expected proportion of 25% and a margin of error of 5%, obtaining a representative sample of 166 first-time mothers with children under six months.

The sampling used was non-probabilistic for convenience, selected based on accessibility to the participants and the availability of time for both the interviewers and the mothers [34]. In addition, the selection of study subjects was carried out considering previously established specific criteria, guaranteeing the relevance and adequacy of the sample in relation to the objectives of the research.

*1)* Inclusion criteria

- New mothers
- Mothers with children under six months of age.
- Mothers located at the National Maternal Perinatal Institute, Laura Rodríguez Dulanto Duksil Maternal and Child Center or the Luis Felipe De Las Casas Health Center.
- Mothers with the physical and mental capacity to participate in the study.
- Mothers who agree to participate in the study by signing the informed consent.

*2)* Exclusion Criteria

- Mothers with multiple children.
- Mothers with children six months and older.
- Mothers who do not belong to the selected health centers.
- Mothers with limitations in reading or writing.
- Mothers who refuse to participate in the study verbally or by not signing the informed consent.

### C. Study Variable(s)

The present study has, as an independent variable the level of anxiety and as a dependent variable the knowledge about breastfeeding, both variables according to their nature are qualitative with an ordinal measurement scale.

*1) Conceptual definition of anxiety level*: It is a temporary emotional condition, characterized by the expression of emotions, nervousness and an increase in the activity of the autonomic nervous system. It functions as a warning signal that alerts about the proximity of a potential danger and enables the person to take action to face the threat [35].

*2) Operational definition of anxiety level*: It is a state of temporary emotional commitment, stimulated by the feeling of danger that occurs in first-time mothers with children under six months of age from the National Maternal Perinatal Institute,

Laura Rodríguez Dulanto Duksil Maternal and Child Center and the Luis Felipe De Las Casas Health Center.

*3) Conceptual definition of knowledge about breastfeeding*: It is the theoretical and practical concepts about breastfeeding acquired throughout life through experiences, study, observation and interaction with the surrounding environment. It plays a fundamental role in decision-making, problem-solving and adaptation to the environment [36].

*4) Operational definition of knowledge about breastfeeding*: they are the set of knowledge related to breastfeeding that determine the behaviors of first-time mothers with children under six months of age from the National Maternal Perinatal Institute, Laura Rodríguez Dulanto Duksil Maternal and Child Center and the Luis Felipe De Las Casas Health Center.

### *D. Measuring Technique and Instrument*

The technique used during data collection is the survey, which is widely used in quantitative and descriptive studies [37]. In addition, an instrument was used for each of the variables.

*1) Anxiety level*: The instrument used to measure this variable is the State-Trait Anxiety Inventory (STAI), which was designed and validated by Charles Spielberger [38] this instrument assesses anxiety with a versatile application, it consists of 40 questions, which are composed of 2 dimensions: Anxiety state, i.e., how one feels at the moment; and Anxiety trait, that is, how one feels in general, uses a 4-point Likert-type scale (from 0 to 3 points). On the state anxiety subscale, item scores ranged from 0 = not at all, 1 = somewhat, 2 = moderately, and 3 = a lot. On the trait anxiety subscale, response options range from 0 = almost never, 1 = sometimes, 2 = often, and 3 = almost always.

For the national context, the validation process of the instrument was carried out through an expert judgment composed of five judges experienced in the thematic area, who issued a rating based on the criteria of relevance, coherence and clarity. Once the answers of the judges were obtained, the validity was calculated with Aiken's V where the values of V close to 1 indicate a perfect agreement of the judges. Finally, the total value of V of Aiken was 0.98, which means that there is a favorable agreement among the judges, which is why the proposed instrument is accepted as valid. In addition, reliability was calculated through a pilot test that included 30 participants, with these data Cronbach's Alpha coefficient was applied to determine the reliability of the questionnaire giving a value of 0.91, which positions it as reliable.

*2) Breastfeeding knowledge*: The questionnaire for the analysis of this variable is called the Breastfeeding Knowledge Instrument developed by Meléndez [39], which measures the level of knowledge about breastfeeding in first-time mothers. This instrument consists of a questionnaire that addresses characteristics of breast milk, benefits of breastfeeding, breastfeeding techniques and practices related to breastfeeding. The questionnaire contains 14 questions that are divided into two dimensions: knowledge about breastfeeding and exclusive breastfeeding practice in mothers. Each item is scored from 0 to 1, and a good knowledge score of 10 to 14 points is established, fair 5 to 9 points, bad 0 to 4 points. In addition, it is determined whether the practice is adequate 7 to 14 points or inadequate 0 to 6 points.

The validity of the questionnaire was determined by the evaluation of a panel of five experts in breastfeeding and childcare, whose scores allowed the calculation of Aiken's V coefficient, obtaining a value of 0.92, which confirms its validity in the population studied. Likewise, reliability was established through a pilot test applied to 30 participants who met the eligibility criteria. The analysis using Cronbach's alpha coefficient yielded a value of 0.89, indicating a high internal consistency and reliability of the instrument. These results ensure that the questionnaire is an accurate and effective tool to assess breastfeeding knowledge and practices in first-time mothers, providing robust and replicable data in future research.

### *E. Bioethical Principles*

Incorporating ethical considerations into research is essential to ensure the proper treatment and protection of participants. This approach ensures that the rights and well- being of the people involved are respected at every stage of the study.

*1) Principle of autonomy*: Participants were free to voluntarily decide whether to participate in the study. They were offered to sign or refuse the informed consent, fully respecting any decision made, reflecting a commitment to ensure their autonomy [40].

*2) Principle of beneficence*: Priority was given to participants having access to reliable and relevant information on anxiety and breastfeeding. This process contributed to the strengthening of their knowledge, promoting their personal benefit and favoring meaningful learning [40].

*3) Principle of non-maleficence*: Measures were implemented to avoid any risk or harm during the interventions. The information collected was used exclusively for academic purposes, ensuring that it was not exposed or publicly disclosed without the express authorization of the participants [40].

*4) Principle of justice*: The participants were treated equally, ensuring equal, respectful and cordial treatment. Likewise, it was verified that the questionnaire was applied only to those participants with the time and willingness to collaborate, promoting a fair and participatory environment [40].

### *F. Previous Coordination*

In the first instance, the pertinent cover letter was sent to the administrative area of the National Maternal and Perinatal Institute, Laura Rodríguez Dulanto Duksil Maternal and Child Center and the Luis Felipe De Las Casas Health Center, attaching approval by the Ethics Committee of the University of Sciences and Humanities, an entity that rigorously evaluates research projects. Through this documentation, the process was carried out to obtain the authorization of the directors and main doctors of the aforementioned health centers, located in Lima.

### G. Data Collection

With the approval of the authorities, the enumerators were able to approach the facilities of the health centers to identify the mothers who meet the criteria indicated and apply the instruments. First, participants were informed about the purpose of the study and informed consent was given, then the confidentiality of their information was ensured and the questionnaire was delivered in a quiet and distraction-free environment. Clear instructions on how to complete the questionnaire were then provided, questionnaires were collected once participants had finished and questionnaires were quickly reviewed to ensure there are no missed responses, the nature of both variables was explained, and educational guidance was provided to reinforce maternal and child care.

### H. Statistical Analysis

The statistical analysis began with the conversion of the collected data to a numerical format for the construction of a matrix that would maintain the order and meaning of the information. This matrix was then translated into Microsoft Excel, which facilitated a preliminary count and initial analysis. Finally, the data were processed using the IBM SPSS Statistics v.25 software, where percentages, absolute and relative frequencies, measures of central tendency and standard deviation were calculated, aligned with the general objective of the study [41].

*5) Multinomial logistic regression model:* It is a statistical technique used to analyze the relationship between a categorical dependent variable with more than two categories and a set of predictor variables. This model allows estimating the probability of belonging to each category, taking one as a reference. It is based on the calculation of probability ratios OR (odds ratios) and adjusts coefficients by means of maximum likelihood [42].

## IV. Results

### A. Sociodemographic Characteristics

Table I shows the sociodemographic data of the mothers who participated in the study, which shows that 8.34% (14) of the mothers are adolescents, 57.23% (95) are young people and 34.34% (57) are adults. Regarding the level of education, 9.04% (15) have incomplete primary or secondary education, 53.01% (88) have completed secondary school, 24.10% (40) are pursuing a technical career, 1.20% (2) have completed a technical career, 11.45% (19) have an incomplete university level and 1.20% (2) have completed university studies. In terms of occupation, 16.27% (27) are housewives, 22.89% (38) are students, 38.55% (64) work and 22.29% (37) study and work. On the other hand, in terms of marital status, 39.76% (66) are single, 49.40% (82) are cohabiting, and 10.84% (18) are married. As for the origin, 80.12% (133) are from Lima, 18.67% (31) are from the province and 1.20% (2) are from abroad. Regarding the type of delivery, 63.25% (105) had a natural birth and 36.75% (61) had a cesarean delivery. Regarding complications in childbirth, 41.57% (69) reported complications and 58.43% (97) had no complications. Regarding the age of the child, 28.31% (47) is from 0 to 1 month, 35.54% (59) is from 2 to 3 months and 56.16% (60) is from 4 to 5 months. Finally, regarding the sex of the child, 62.05% (103) is male and 37.95% (63) is female.

TABLE I Sociodemographic Characteristics of First-Time Mothers with Children under Six Months of Age in Lima

| Sociodemographic characteristics | n=166 | |
|---|---|---|
| | fi | % |
| **Age** | | |
| Adolescent | 14 | 8.43 |
| Young | 95 | 57.23 |
| Adult | 57 | 34.34 |
| **Level of education** | | |
| Secondary and/or Primary Incomplete | 15 | 9.04 |
| Complete Secondary School | 88 | 53.01 |
| Ongoing Technician | 40 | 24.10 |
| Complete Technician | 2 | 1.20 |
| Incomplete University | 19 | 11.45 |
| Complete University | 2 | 1.20 |
| **Occupation** | | |
| Housewife | 27 | 16.27 |
| Studies | 38 | 22.89 |
| Works | 64 | 38.55 |
| Study and work | 37 | 22.29 |
| **Marital status** | | |
| Single | 66 | 39.76 |
| Cohabitant | 82 | 49.40 |
| Married woman | 18 | 10.84 |
| **Origin** | | |
| File | 133 | 80.12 |
| Province | 31 | 18.67 |
| Foreigner | 2 | 1.20 |
| **Type of delivery** | | |
| Normal delivery | 105 | 63.25 |
| Cesarean delivery | 61 | 36.75 |
| **Complications in childbirth** | | |
| Yes | 69 | 41.57 |
| No | 97 | 58.43 |
| **Age of the child** | | |
| 0 to 1 month | 47 | 28.31 |
| 2 to 3 months | 59 | 35.54 |
| 4 to 5 months | 60 | 56.16 |
| **Sex of the child** | | |
| Male | 103 | 62.05 |
| Female | 63 | 37.95 |

### B. Breastfeeding Knowledge

Fig. 1 shows the distribution of the level of knowledge about breastfeeding in first-time mothers with children under six months of age. The results reveal that 13.86% (23) of the participants have a good knowledge about breastfeeding, while the majority, equivalent to 71.08% (118), show a regular level of knowledge. On the other hand, 15.06% (25) of the mothers evaluated have poor knowledge in this area.

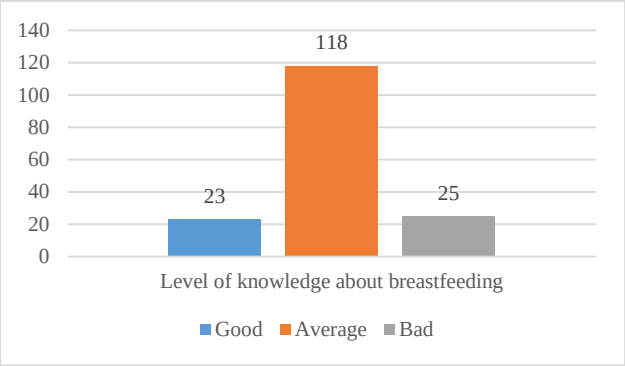


Fig. 1. Level of knowledge about breastfeeding.

### C. Anxiety, Status and Knowledge about Breastfeeding According to Sociodemographic Characteristics

Fig. 2 shows the distribution of the level of state anxiety and knowledge about breastfeeding according to the age of the mothers, grouped into adolescents, young people and adults. It can be identified that the group of adolescents with state anxiety is made up of 14 mothers, which represents 8.43% (0.60% (1) with low state anxiety and medium knowledge, 1.205% (2) with moderate anxiety and low knowledge, 5.42% (9) with moderate anxiety and medium knowledge, 1.205% (2) with moderate anxiety and good knowledge). The group of young people with state anxiety is composed of 95 mothers or 57.23% (1.81% (3) with low anxiety and bad knowledge, 6.02% (10) with low anxiety and medium knowledge, 2.41% (4) with low anxiety and good knowledge, 5.42% (9) with moderate anxiety and bad knowledge, 24.10% (40) with moderate anxiety and medium knowledge, 6.02% (10) with moderate anxiety and good knowledge, 1.205% (2) with high anxiety and bad knowledge, 8.43% (14) with high anxiety and medium knowledge, 1.81% (3) with high anxiety and good knowledge). In the group of adults with state anxiety, 57 mothers or 34.34% (1.81% (3) with low anxiety and bad knowledge, 3.01% (5) with low anxiety and medium knowledge, 0.60% (1) with low anxiety and good knowledge, 1.205% (2) with moderate anxiety and bad knowledge, 15.66% (26) with moderate anxiety and medium knowledge, 1.81% (3) with moderate anxiety and good knowledge, 2.41% (4) with high anxiety and poor knowledge, 7.83% (13) with high anxiety and medium knowledge).

Table II presents the distribution of anxiety, status, and knowledge about breastfeeding according to the participants' occupation. In the group of housewives, 1.81% (3) have low state anxiety, with 2 people with bad knowledge and 1 regular. 9.64% (16) had moderate anxiety, with 5 people having bad knowledge, 10 regular and 1 good. 4.82% (8) had high anxiety, with 7 people with regular knowledge and 1 good. In the group of mothers who study, 4.22% (7) have low anxiety, with 5 people with regular knowledge and 2 with good knowledge. 12.65% (21) had moderate anxiety, with 1 person having bad knowledge, 16 regular and 4 good. 6.02% (10) had high anxiety, with 1 person with poor knowledge, 8 regular and 1 good. In working mothers, 5.42% (9) have low anxiety, with 1 person having bad knowledge, 6 fair and 2 good. 25.90% (43) had moderate anxiety, with 5 people with poor knowledge, 32 regular and 6 good. 7.23% (12) had high anxiety, with 5 people having poor knowledge and 7 having regular knowledge. Mothers who study and work with low anxiety constitute 4.82% (8), with 3 people with bad knowledge, 4 fair and 1 good. 13.86% (23) had moderate anxiety, with 2 people with poor knowledge, 17 regular and 4 good. 3.61% (6) had high anxiety, with 5 people with regular knowledge and 1 good one.

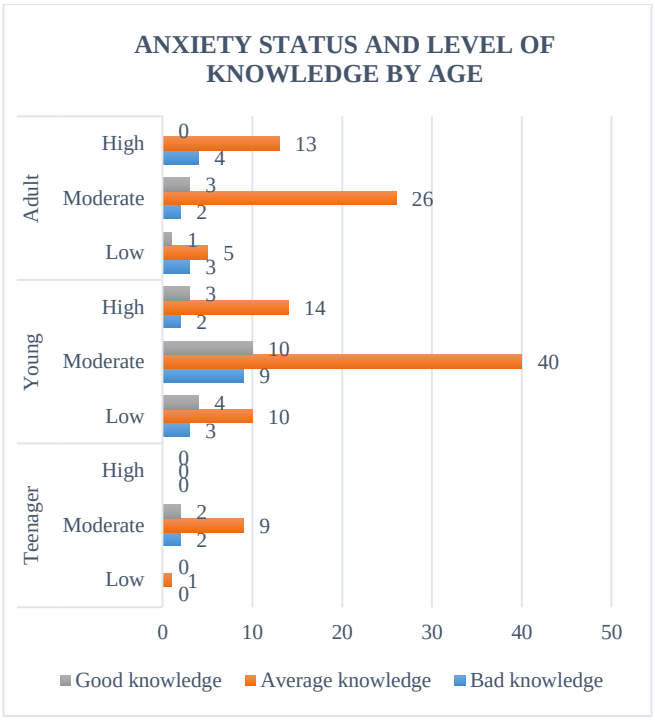


Fig. 2. Level of anxiety, status and knowledge about breastfeeding by age.

TABLE II ANXIETY, STATE AND KNOWLEDGE ABOUT BREASTFEEDING BY OCCUPATION

| Occupation | State anxiety | Level of knowledge | | | | |
|---|---|---|---|---|---|---|
| | | Bad boy | Regular | Well | fi | % |
| Housewife | Casualty | 2 | 1 | 0 | 3 | 1.81 |
| | Moderate | 5 | 10 | 1 | 16 | 9.64 |
| | Loud | 0 | 7 | 1 | 8 | 4.82 |
| Studies | Casualty | 0 | 5 | 2 | 7 | 4.22 |
| | Moderate | 1 | 16 | 4 | 21 | 12.65 |
| | Loud | 1 | 8 | 1 | 10 | 6.02 |
| Works | Casualty | 1 | 6 | 2 | 9 | 5.42 |
| | Moderate | 5 | 32 | 6 | 43 | 25.90 |
| | Loud | 5 | 7 | 0 | 12 | 7.23 |
| Study and work | Casualty | 3 | 4 | 1 | 8 | 4.82 |
| | Moderate | 2 | 17 | 4 | 23 | 13.86 |
| | Loud | 0 | 5 | 1 | 6 | 3.61 |
| Total | | 25 | 118 | 23 | 166 | 100 |

### D. Trait Anxiety and Knowledge about Breastfeeding According to Sociodemographic Characteristics

Fig. 3 shows the distribution of the level of trait anxiety and knowledge about breastfeeding by age groups. It can be identified that the group of adolescents with trait anxiety is made up of 14 mothers, which represents 8.43% (0.60% (1) with moderate anxiety and bad knowledge, 5.42% (9) with moderate anxiety and medium knowledge, 0.60% (1) with moderate anxiety and good knowledge, 0.60% (1) with high anxiety and bad knowledge, 0.60% (1) with high anxiety and medium knowledge, 0.60% (1) with high anxiety and good knowledge). The group of young people with trait anxiety is composed of 95 mothers or 57.23% (2.41% (4) with low anxiety and medium knowledge, 5.42% with moderate anxiety and poor knowledge, 22.29% (37) with moderate anxiety and medium knowledge, 7.23% (12) with moderate anxiety and good knowledge, 3.01% (5) with high anxiety and bad knowledge, 13.86% (23) with high anxiety and medium knowledge, 3.01% (5) with high anxiety and good knowledge). In the group of adults with trait anxiety, 57 mothers or 34.34% (1.205% (2) with low anxiety and bad knowledge, 2.41% (4) with low anxiety and medium knowledge, 1.205% (2) with moderate anxiety and bad knowledge, 12.04% (20) with moderate anxiety and medium knowledge, 1.81% (3) with moderate anxiety and good knowledge, 3.01% (5) with high anxiety and bad knowledge, 12.04% (20) with high anxiety and medium knowledge, 0.60% (1) with high anxiety and good knowledge).

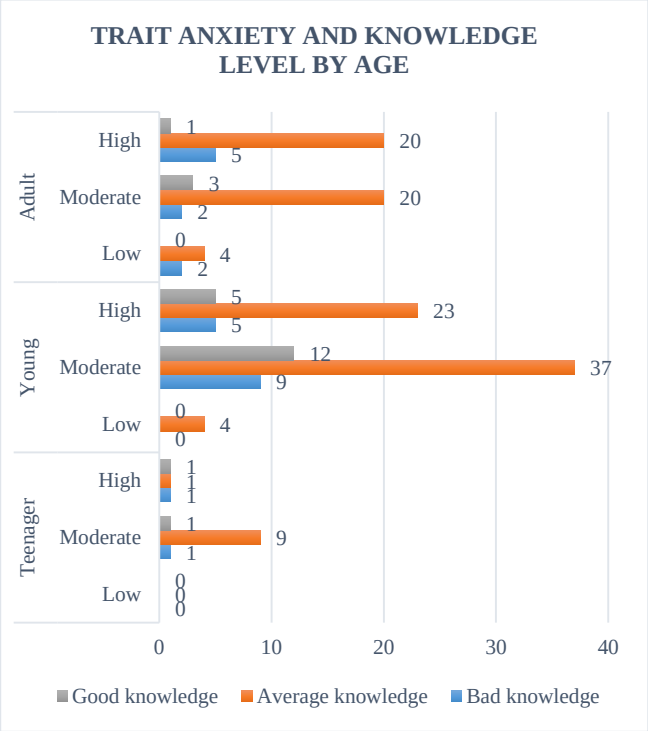


Fig. 3. Level of anxiety trait and knowledge about breastfeeding by age.

Table III presents the distribution of trait anxiety and knowledge about breastfeeding according to the participants' occupation. In the group of housewives, 0.60% (1) have low trait anxiety, with 1 person having poor knowledge. 5.42% (9) had moderate anxiety, with 2 people with bad knowledge, 6 fair and 1 good. 10.24% (17) had high anxiety, with 4 people with bad knowledge, 12 regular and 1 good. In the group of mothers who studied, 0.60% (1) had low anxiety, with 1 person with regular knowledge. 14.46% (24) had moderate anxiety, with 1 person having bad knowledge, 17 regular and 6 good. 7.83% (13) had high anxiety, with 1 person having bad knowledge, 11 regular and 1 good. In working mothers, 3.61% (6) have low anxiety, with 1 person having poor knowledge and 5 having regular knowledge. 22.89% (38) had moderate anxiety, with 5 people with poor knowledge, 28 regular and 5 good. 12.05% (20) had high anxiety, with 5 people having bad knowledge, 12 regular and 3 good. Mothers who study and work with low anxiety constitute 1.21% (2), with people with 2 people with regular knowledge. 13.86% (23) had moderate anxiety, with 4 people with poor knowledge, 15 regular and 4 good. 7.23% (12) had high anxiety, with 1 person with bad knowledge, 9 regular and 2 good.

TABLE III TRAIT ANXIETY AND KNOWLEDGE ABOUT BREASTFEEDING BY OCCUPATION

| Occupation | Trait anxiety | Level of knowledge | | | | |
|---|---|---|---|---|---|---|
| | | Bad boy | Regular | Well | fi | % |
| Housewife | Casualty | 1 | 0 | 0 | 1 | 0.60 |
| | Moderate | 2 | 6 | 1 | 9 | 5.42 |
| | Loud | 4 | 12 | 1 | 17 | 10.24 |
| Studies | Casualty | 0 | 1 | 0 | 1 | 0.60 |
| | Moderate | 1 | 17 | 6 | 24 | 14.46 |
| | Loud | 1 | 11 | 1 | 13 | 7.83 |
| Works | Casualty | 1 | 5 | 0 | 6 | 3.61 |
| | Moderate | 5 | 28 | 5 | 38 | 22.89 |
| | Loud | 5 | 12 | 3 | 20 | 12.05 |
| Study and work | Casualty | 0 | 2 | 0 | 2 | 1.21 |
| | Moderate | 4 | 15 | 4 | 23 | 13.86 |
| | Loud | 1 | 9 | 2 | 12 | 7.23 |
| Total | | 25 | 118 | 23 | 166 | 100 |

### E. Multinomial Logistic Regression Model

The established model was applied to detect whether the level of anxiety in mothers influences the level of knowledge about breastfeeding or vice versa, in addition to the relevance of sociodemographic data. In this process, an association of these variables has been found for both state anxiety and trait anxiety.

*6) Anxiety state*: It has been identified that the predominant factors affecting state anxiety are sociodemographic in nature. This process can be described through the following formula:

$$AE = 1.03 - 0.828(x1) - 0.149(x2) + 0.2148657(x3)$$

where:

AE: State Anxiety

x1: Occupation

x2: Provenance

x3: Complications

Through this calculation, it can be concluded that the Multinomial Logistic Regression Model is adequate, since it presents at least a significant positive value, which is detailed in the following table.

TABLE IV REGRESSION MODEL FOR STATE ANXIETY BASED ON SOCIODEMOGRAPHIC DATA

| Sociodemographic data | Anxiety State |
|---|---|
| | P value (< 0.05) |
| Occupation | 0.083 |
| Origin | 0.167 |
| Complications | 0.026 |

Table IV presents the relationship between the sociodemographic data analyzed in the statistical model and the mothers' state anxiety. It can be detected that the p-value of significance is greater than 0.05 in the variables, with the exception of complications in childbirth p = 0.026, which statistically evidences those complications in childbirth are associated with having state anxiety.

TABLE V ANXIETY STATUS AND COMPLICATIONS IN CHILDBIRTH

| Complications in childbirth | Anxiety State |
|---|---|
| | Odds Ratio (OR > 1) |
| YES | 1.025753 |
| NO | 0.274951 |

Table V presents the relationship between complications in childbirth and state anxiety. It can be detected that the Odds Ratio is greater than unity in mothers who HAVE had complications in childbirth with an OR of 1.025753, which means that statistically mothers who have presented complications in childbirth are likely to have state anxiety.

*7) Trait anxiety:* In relation to trait anxiety, sociodemographic factors have been identified that significantly influence its manifestation. This process can be described by the following formula:

$$AR = 1.23501 - 0.1120824(x1) + 0.1674339(x2)$$

where:

AR: Trait Anxiety

x1: Occupation

x3: Complications

Through this calculation, it can be stated that the Multinomial Logistic Regression Model is acceptable, since it has at least one positive value of significance, which is detailed in the table below.

TABLE VI REGRESSION MODEL FOR TRAIT ANXIETY BASED ON SOCIODEMOGRAPHIC DATA

| Sociodemographic data | Trait Anxiety |
|---|---|
| | P value (< 0.05) |
| Occupation | 0.013 |
| Complications | 0.066 |

Table VI presents the relationship between the sociodemographic data analyzed in the statistical model and maternal trait anxiety. It can be detected that the p-value of significance is less than 0.05 in occupation with a p-value = 0.013, which statistically evidences that the mothers' occupation is associated with having trait anxiety.

TABLE VII TRAIT ANXIETY AND OCCUPATION

| Occupation | Trait Anxiety |
|---|---|
| | OR (Odds Ratio > 1) |
| Housewife | 0.8416789 |
| Studies | 1.149548 |
| Works | 0.3544152 |
| Study and work | 0.7960873 |

Table VII presents the relationship between mothers' occupation and trait anxiety. It can be detected that the Odds Ratio is less than one unit in the variables, with the exception of the mothers who study, since in them there is an OR of 1.149548, which means that statistically the mothers who study have a higher probability of having trait anxiety.

## V. DISCUSSION

This study evaluated 166 first-time mothers with children under six months, with the aim of analyzing the relationship between the level of anxiety and knowledge about breastfeeding. The results did not show a significant influence of anxiety on breastfeeding knowledge, which led to the rejection of the initial hypothesis. However, relevant data were found that suggest a relationship between the level of anxiety and the sociodemographic characteristics of the mothers, which opens new lines of research to explore these factors in depth.

In this sense, it was estimated that 57.23% of first-time mothers are between 18 and 26 years old, which classifies them as young according to the WHO [43]. However, this data contrasts with the findings of [27], which reported a mean age of 34.2 years, and with [28], where the average age was 32.9 years, classifying the mothers as adults. This difference could be linked to the high incidence of teenage pregnancies in Peru, a phenomenon that, although it has decreased in recent years, is still significantly higher than in other countries [44].

Regarding the educational level of the mothers, 53.01% have completed secondary school, which coincides with the predominant age group in this study, since youth is usually linked to higher education, as indicated in [27], where 61.5% of the mothers had university studies. However, in our study, only 22.89% of the mothers indicated studying as an occupation, while 38.55% worked, which could reflect the need for economic income faced by young mothers within the social and economic context of Peru.

It was observed that 63.25% of the mothers had a normal delivery; however, of the total number of mothers with normal delivery and cesarean section, 41.57% experienced complications, which shows that normal delivery does not guarantee the absence of complications. In addition, 56.16% of the children were between 4 and 5 months old, a crucial stage in which children require exclusive care and reinforcement of breastfeeding to prevent problems such as anemia. These situations generate psychological distress in mothers, especially if they are first-time mothers, and as pointed out [30], maternal

anxiety disorders must be addressed before or during pregnancy to prevent negative impacts on the well-being of the mother and child.

The analysis of breastfeeding knowledge in first-time mothers showed that 71.08% of mothers with children under six months of age have regular knowledge about breastfeeding, which coincides with the findings of [22], where 80.4% of mothers also had regular knowledge. This reflects the predominance of basic or insufficient knowledge of breastfeeding among mothers, which highlights the need to reinforce this knowledge through support programs that promote a better understanding and practice of breastfeeding in the early stage of motherhood.

On the other hand, the study revealed that all mothers have levels of anxiety, both state and trait, although in different intensities. This finding is justified by the significant changes that motherhood implies in women's emotional and psychological lives. Motherhood can trigger both adaptive and stress responses, raising anxiety levels, especially in those with a greater genetic or historical predisposition to experience it. This situation affects the motherhood process, as evidenced in [29], who pointed out that anxiety has negative effects on child upbringing and development.

In mothers with state anxiety, it is identified that 24.10% are young people with moderate state anxiety and medium knowledge about breastfeeding. In addition, 25.90% (43) of mothers with this type of anxiety work and of these 32 have regular knowledge. As for mothers with trait anxiety, 22.29% are young people with moderate trait anxiety and medium knowledge about breastfeeding. Likewise, 22.89% (38) of these mother's work, and 28 of them have regular knowledge. These findings suggest that there is a relationship between anxiety, maternal age, knowledge about breastfeeding and occupation, since these factors can generate tension that decreases when stressors are resolved, although anxiety can persist in the long term.

In relation to the logistic regression model, it has been shown to be adequate for analyzing state anxiety, since complications during childbirth show a statistically significant relationship with state anxiety, evidenced by a p-value of 0.026. This finding is reinforced by the individual analysis of complications in childbirth, where an OR of 1.025753 indicated that mothers who experienced complications have a higher chance of developing state anxiety. This result can be explained by the fact that complications in childbirth pose a threat to both mother and child, acting as a strong stimulus for episodes of anxiety.

The regression model for trait anxiety has also proven to be adequate, as a statistically significant relationship was found between the mother's occupation and trait anxiety, with a p- value of 0.013. This result is reinforced by the individual analysis of the type of occupation, in which an OR of 1.149548 showed that mothers who study are more likely to present trait anxiety. This may be explained by the fact that trait anxiety persists over time, possibly caused by academic stresses, which persist into motherhood.

## VI. Conclusion

This study sought to analyze the relationship between the level of anxiety and knowledge about breastfeeding in first-time mothers with children under six months. However, no conclusive results were found to support a significant correlation between the two variables. Consequently, the relationship between anxiety and sociodemographic factors was further explored. The absence of a positive correlation between anxiety and breastfeeding knowledge suggests that, although anxiety does not necessarily inhibit learning, there is scope to improve knowledge through intervention strategies.

The results of the study indicate that the experience of motherhood, especially for first-time mothers, presents significant emotional challenges that need to be properly identified and supported. Therefore, the implementation of accessible psychological support programs becomes essential, encompassing both individual and group activities, stress management techniques, and peer support groups. These programs must be adapted to the diverse circumstances of the mothers, taking into account factors such as age, history of complications in childbirth, occupation and educational level. In addition, it is crucial that these interventions are culturally sensitive and adapted to the social and cultural reality of Peru.

A holistic approach that strengthens both the mother's knowledge of breastfeeding and the motherhood process would not only improve the emotional well-being of new mothers, but would also have a positive impact on the health and optimal development of babies under six months of age. To address this challenge, it is crucial to provide broader education, access to reliable information, and greater support from health professionals and society at large. This knowledge would benefit not only mothers and their children, but also society, reducing the burden on the health system and increasing awareness of the importance of child nutrition.

Finally, this study opens the door to future longitudinal studies that could examine how anxiety and knowledge levels evolve over time, especially under psychological and educational support programs. In addition, it would be valuable to incorporate additional socio-demographic factors, such as family or partner support, specific economic situation and mothers' previous experiences. These factors could have a significant influence on anxiety and knowledge levels, which would improve the conditions of mothers and enrich understanding in this field of study.

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# Economic Growth and Fiscal Policy in Peru: Prediction Using Machine Learning Models

Fidel Huanco Ramos[1], Yesenia Valentin Ccori[2], Henry Shuta Lloclla[3],
Martha Yucra Sotomayor[4], Ilda Mamani Uchasara[5]
Universidad De San Martín De Porres, Arequipa, Perú[1]
Universidad Nacional De San Antonio Abad De Cusco, Cusco, Perú[2]
Universidad Nacional Del Altiplano, Puno, Perú[3, 4]
Universidad Peruana Unión, Juliaca, Peru[5]

***Abstract*—The empirical literature presents several indicators related to fiscal policy and economic growth. The paper aims to predict Peru's economic growth using fiscal policy variables. For this purpose, open data from the Central Reserve Bank of Peru was used, data preprocessing and the study used Python programming through Google Colab to evaluate eight machine learning models. Metrics such as Root Mean Square Error (RMSE), Mean absolute error (MAE), Mean square error (MSE), and Coefficient of Determination ($R^2$) were used to measure their performance. In addition, SHapley Additive exPlanations (SHAP) was applied to interpret the importance of macroeconomic variables. The results show that the K-Nearest Neighbors (KNN) model obtained the best performance, with an $R^2$ of 0.972 and low prediction errors. In the same way, important variables in fiscal policy such as Net Debt, Liabilities, and Interest on External Debt were identified. In conclusion, the study shows that KNN and Ensemble Bagging are highly effective models for predicting Peru's economic growth.**

***Keywords*—Machine learning; predictive models; fiscal policy; economic growth**

## I. Introduction

The relationship between fiscal policy and economic growth has been the subject of study for decades, constituting an important topic in contemporary economics. Fiscal policy, understood as the set of decisions related to taxation and public spending, has a direct influence on economic activity and social welfare. According to Barro [1], efficient management of fiscal policy can stimulate long-term economic growth, while an inappropriate approach can lead to imbalances and recessions. Furthermore, according to Caprioli [2], considered a closed production economy, fiscal authority, infinitely live agents, and the absence of capital, provides a simplified framework for analysing the effects of fiscal policies in an economy.

The government has to match an exogenous stream of public spending through proportional taxes on labor income and government bonds. It pursues optimal taxation, given the initial amount of debt, it chooses policy instruments to maximize consumer welfare. However, the analysis of the impact of these policies has become more complex due to increased volatility in markets and non-linear interrelationships between economic variables [3], [4].

Given the characteristic non-linear behavior of many economic variables, new methodologies based on artificial neural networks have been explored since the 1990s [5]. They therefore offer a significant advantage by allowing the modelling of both linear and non-linear relationships between the input and output variables of a system. In this perspective, it has proven valuable in highly volatile environments, such as financial markets, where economic variables often exhibit complex and non-linear patterns [6]. In this sense, the technology contributes to dynamic macroeconomic forecasting [7], under the approach of scientific, reliable, and complete historical statistics.

Machine learning and artificial intelligence have opened up new possibilities for economic analysis. Models such as K-Nearest Neighbors (KNN), Ensemble Bagging, and Random Forest allow large volumes of data to be processed and non-linear interactions to be modelled with greater accuracy. In addition, the incorporation of explanatory techniques such as SHAP (SHapley Additive exPlanations) facilitates the interpretation of models, offering a deeper understanding of the factors driving economic growth and has positioned itself as an innovative tool for managing large volumes of data and uncovering hidden patterns [8], [9]. This methodology has proven to be effective in a number of fields, including economics, where it can provide more accurate and adaptive predictions for public policy formulation [10], [11]. In addition, studies suggest the use of machine learning algorithms to improve the ability to forecast and predict the impact of fiscal policies on economic growth, overcoming the limitations of conventional econometric models [12], [13].

The main objective of the study is to predict Peru's economic growth using fiscal policy variables. To this end, it seeks to rigorously evaluate how the main fiscal policy variables, such as public spending, tax collection, and the fiscal deficit, influence the country's economic development. Furthermore, this study not only seeks to contribute to the understanding of the relationship between fiscal policy and economic growth in Peru, but also to offer practical recommendations that can guide fiscal decision-making to promote sustainable economic development through the use of machine learning.

## II. Literature Review

### A. Artificial Intelligence Theory

The application of artificial intelligence (AI) techniques in the prediction of fiscal policies and economic growth has

experienced exponential growth, consolidating itself as a highly relevant field of research [14], [15]. AI is used to analyze large volumes of data, identifying patterns and trends that enable a country's decision-making. Machine learning algorithms can analyze historical data such as tax collection, public spending, and economic indicators to predict how these factors will behave under different scenarios. According to Kaliuzhniak [16], this research explores the use of AI, neural networks, and machine learning in economic forecasting, highlighting the importance of making appropriate decisions in social management. Similarly, Aliyev [17], discusses how AI, machine learning and data mining are applied in economic modelling and prediction of economic growth and fiscal policy in the context of the Industrial.

### *B. Theory of Fiscal Policy*

Fiscal policy, combined with monetary policy, has long been one of the main instruments used by governments to intervene and influence economic activity [18]. Thus, depending on economic conditions, public expenditures and taxes are used to influence the economy in the direction of expansion or contraction [19]. However, the views and theories on the effectiveness of this fiscal instrument have often been contradictory [20].

Thus, John Maynard Keynes provided a theoretical foundation for the use of fiscal policy, demonstrating that public expenditures and taxes are effective tools for regulating economic cycles [21]. According to this theory, insufficient aggregate demand is the primary cause of economic recessions. Therefore, increasing public expenditures or encouraging private spending through tax cuts enhances purchasing power and, consequently, consumption, stimulating short-term economic growth [22], [23]. In fact, for Keynesians, there is a relationship between the level of expenditure and national income (and, consequently, employment), as an increase in expenditure stimulates household consumption and encourages producers to expand their production to meet additional demand, thereby creating jobs. According to Xin Li [24], fiscal policies have been and will continue to be an essential component in mitigating the effects of the pandemic on the Chinese economy. However, their impact will be gradual and a balance between fiscal stimulus and pandemic control measures will need to be maintained.

### *C. Economic Growth Theory*

It is the sustained increase in the production of goods and services in an economy over time. It is generally measured through real Gross Domestic Product (GDP), which represents the total value of final goods and services produced in a country during a given period, adjusted for inflation [25] . Likewise, the Solow-Swan model is an exogenous economic growth model, while the endogenous growth theory explains economic growth from factors internal to a country [26]. The latter emphasizes the importance of capital accumulation and technological progress as engines of economic growth, without relying exclusively on external factors such as foreign investment or international trade [27]. Similarly, the Harrod-Domar model is an economic model that explains how the rate of investment influences productive capacity and aggregate demand [28]. It focuses on investment as the main driver of economic growth, highlighting the relationship between savings, investment, and GDP growth [29]. In addition, the British economist John Maynard Keynes said that capital formation is a fundamental element of growth analysis, and his argument is simple. Investment will increase employment levels. According to the principle of effective demand, investment is a variable that reduces the gap between the level of income or the level of production and the level of consumption [30].

### *D. Limitations and Contributions of this Study*

While the literature demonstrates significant advances in the application of artificial intelligence and economic models for the analysis of economic growth and fiscal policy, limitations persist that warrant the development of new approaches [31]. Most studies focus on international contexts or developed economies, neglecting particularities of developing countries such as Peru. In addition, many studies omit important fiscal policy variables, which limits the accuracy and applicability of predictive models. Likewise, there are few explanatory techniques that allow interpreting the results of predictive models, which limits their usefulness in governmental decision-making. Faced with these gaps, the present study proposes an approach that incorporates multiple machine learning algorithms, together with the use of SHAP as an explanatory technique, applied specifically to the Peruvian context [32]. This methodology not only improves the ability to predict economic growth, but also makes it possible to interpret the relative impact of fiscal variables, providing valuable tools for the formulation of more effective public policies.

## III. MATERIALS AND METHODOLOGY

The materials used in the research include open data from the Central Reserve Bank of Peru (BCRP) for the period 1990-2023, consisting of annual time series on fiscal policy and economic growth. Implemented with the following libraries: Numpy, Pandas, Matplotlib, Seaborn, SHAP, and Scikit-learn in colab Google Python. Based on four processes:

### *A. Data and Variables of the Study*

The data for the study were obtained from the Banco Central de Reserva del Peru (BCRP), since the data are reliable and consist of a set of economic resources of the central government, allocated to various sectors of the executive branch in order to meet their objectives, such as the maintenance of infrastructure, the provision of public services and the payment of debts, among others. Public spending, tax revenues, public investment and public debt are fundamental components of fiscal policy, which directly influence economic growth. It is also divided into various categories and subcategories that allow a detailed breakdown of the use of resources. In this case, the following variables are identified: Central Government Non-Financial Expenditure.

Central Government Remuneration

Central Government Goods and Services

Central Government Transfers

Central Government Capital Expenditure

Central Government Gross Capital Formation

Other Central Government Capital Expenditure

Central Government Total Interest

Interest on Central Government Domestic Debt

Interest on Central Government External Debt

Total Central Government Expenditure

Non-Financial Expenses of the Rest of the Central Government

Non-Financial Current Expenditure of Rest of Central Government

Capital Expenditure of Rest of the Central Government

Interest of Rest of the Central Government

Tax Revenue of Rest of the Central Government

Income Tax

Wealth Tax

Tax on Exports

Tax on Imports

General Sales Tax - IGV

IGV - Internal

IGV - Imports

Selective Consumption Tax - ISC

ISC - Fuels

ISC - Others

Other Tax Revenues

Refunds

Non-Tax Revenues

Total Central Government Current Revenues

Public Sector - Public Investment

Assets

Liabilities

Net Debt

Gross Domestic Product (Real GDP)

### B. Data Pre-processing

It ensures that Machine Learning models work with appropriate and well-structured data. To do this, it starts with loading the dataset from an Excel file stored in Google drive, followed by the separation of the predictor features (X) and the target variable (y). Subsequently, the dataset is split into training (80 per cent) and testing (20 per cent) using train_test_split to ensure adequate generalization of the model. To standardize the features, StandardScaler is applied, fitting the transformation with the training data and applying it to the test set, ensuring that all variables have mean zero and standard deviation one. This process improves the numerical stability and performance of Machine Learning models by eliminating inconsistent scaling in the data.

### C. Training of Machine Learning Models

The selection of machine learning models for the analysis focused on those capable of predicting various economic variables, based on a set of fiscal policy indicators that include public spending, tax revenue, public investment, and public debt. The models are presented below:

Gaussian Process Regression (GPR) is a powerful statistical technique with a Bayesian approach, used in machine learning and data analysis to predict unknown values from observed data [33]. Its ability to model uncertainty and capture complex relationships makes it ideal for a wide range of applications [34].

Given a training data set {X, y}, the model assumes that the output values y follow a joint Gaussian distribution:

$$y \sim N(\mu(X), K(X,X) + \sigma^2 I) \quad (1)$$

where, (μ(X) is the mean function, usually assumed to be 0, K(X, X) is the kernel-based covariance matrix and $\sigma^2 I$ I is the noise variance (I is the identity matrix).

Then, it is to predict a new point X*, the conditional distribution is:

$$\hat{y}^* = K(X^*, X)K(X,X)^{-1} \quad (2)$$

where, $K(X^*, X)$ represents the covariance between the new points X* and the training data, $K(X,X)^{-1}$ y is the estimate of the values based on the previous data.

Fine Trees are a type of supervised learning model based on decision trees, where the tree is allowed to grow to a considerable maximum depth (in this case, max_depth=10) to capture complex relationships without overfitting. It is based on recursive feature space partitioning using impurity reduction. This model is useful in time series, economic forecasting, pattern recognition, and tabular data analysis [34].

$$f(X) = \sum_{i=1}^{N} c_i 1(X \epsilon R_i) \quad (3)$$

where, N is the total number of terminal regions.

Random Forest is a machine learning algorithm based on a set of decision trees that improves the accuracy and stability of predictions by reducing overfitting [35]. In this study, a Random Forest machine learning algorithm is used to estimate economic growth in Peru, which is considered a function approximation (regression) problem.

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(X) \quad (4)$$

where, $\hat{y}$ represents the predicted economic growth, $N$ is the total number of trees in the forest and $T_i(X)$ is the prediction of $i - ésimo$

The Linear Support Vector Machine (SVM) is a machine learning model that seeks to find an optimal hyper plane to

separate data into different classes (classification) or make numerical predictions (regression) [36]. In regression (Linear SVR), instead of classifying, the model finds a hyperplane that minimizes the error within a margin ϵ, ignoring small deviations and penalizing larger errors [37]. Its main advantage is its ability to handle high-dimensional data and avoid overfitting by regularizing its parameters.

$$f(X) = w^T X + b \quad (5)$$

where, *w* and *b* are the parameters that are tuned to minimize the error. To avoid overfitting, Linear SVR employs an insensitive loss function $\epsilon$ and a hyperparameter C that controls the penalty for out-of-range errors. This model is useful in economic forecasting, time series, and financial analysis problems, as it offers a robust solution to data variability.

The MLPRegressor (Artificial Neural Network for Regression) model is a multi-layered artificial neural network used for regression tasks. It consists of an input layer, one or more hidden layers, and an output layer, where each neuron applies a nonlinear transformation to the data using activation functions such as ReLU or sigmoid.

Given an input set X, the three-layer (input, hidden, and output) neural network is defined as:

$$h^l = f(W^l h^{(l-1)} + b^{(l)}) \quad (6)$$

where, $h^l$ is the activation of layer *l*, $W^l$ is the weight matrix of layer l, $b^l$ is the bias vector and f(.) is the activation function.

For the output layer in regression, the final prediction is:

$$\hat{y} = W^L h^{(L-1)} + b^{(L)} \quad (7)$$

where, ***L*** is the final layer.

The KNeighborsRegressor is a machine learning model based on the k-Nearest Neighbors (KNN) algorithm, used for regression tasks [9], [38]. Instead of learning an explicit feature during training, it stores the data and predicts the value of a new instance by calculating the average of the k nearest neighbors in the feature space [39].

For an input X, the prediction is defined as:

$$\hat{y} = \frac{1}{k}\sum_{i=1}^{k} y_i \quad (8)$$

where, $k$ is the number of neighbors y $y_i$ are the target values of the k nearest neighbors. The model uses a distance metric (by default, Euclidean) to find the nearest neighbors and may weight their contribution according to closeness.

The BaggingRegressor is an ensemble learning model based on the Bootstrap Aggregating (Bagging) technique, which improves the accuracy and stability of regression models by reducing the variance [40].

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} f_b(x) \quad (9)$$

$\hat{y}$: Final prediction of the Bagging model.

B: Total number of base models (estimators).

$f_b(x)$: Base model prediction bbb for an input x

$\sum_{b=1}^{B} f_b(x)$: Suma de las predicciones de todos los modelos base

$\frac{1}{B}$: Average of the predictions.

Under this approach it helps to reduce the variance of the base model, making it more robust and stable compared to a single regression model.

A "Coarse Decision Tree" refers to a decision tree with limited depth, meaning it has a small number of levels or splits [41].

$$\hat{y}(x) = \sum_{m=1}^{M} c_m . 1(x \epsilon R_m) \quad (10)$$

$\hat{y}(x)$: Decision tree prediction for an input *x.*

M: Total number of regions (or leaf nodes) created by the tree. $R_m$: *m-th* region into which the feature space is divided.

$c_m$: Output value for the region $R_m$ (usually the average of the training values in that region).

$1(x \epsilon R_m)$: Indicator function, which is *1* if *x* belongs to the region $R_m$ and 0 otherwise.

### *D. Model Evaluation*

i. Root Mean Square Error (RMSE)

RMSE is a widely used metric that measures the average magnitude of inter-predicted errors $y_i$ and observed $\bar{y}_i$ values [42]. The accuracy of the model is assessed comprehensively, with lower values indicating better performance [43].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \quad (11)$$

where, ***N*** is the total number of observations.

ii. Mean absolute error (MAE)

MAE quantifies the mean absolute difference between predicted and predicted$\bar{y}_i$ and observed $y_i$ values, providing a measure of the accuracy of the model without considering the direction of the errors [44].

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \bar{y}_i| \quad (12)$$

where, N is the total number of observations.

iii. Mean square error (MSE)

MSE measures the average of the squares of the inter-predicted errors $\bar{y}_i$ and observed $y_i$ values, providing a measure of the model's accuracy that emphasizes errors larger than MAE [45].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i)^2 \quad (13)$$

iv. Coefficient of Determination ($R^2$)

Often denoted as $R^2$, assesses the proportion of the variance in the dependent variable (economic growth) that is predictable from the independent variables (public expenditure). It ranges between 0 and 1, where higher values indicate better explanatory power [46], [47].

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \quad (14)$$

where, N is the total number of observations $y_i$ is the observed value, $\bar{y}_i$ es el valor, Foreseen $\bar{y}_i$ is the mean of the observed values.

These performance indices jointly assess the predictive accuracy of the model, highlighting different aspects of the prediction errors

### E. Interpretation of Results

SHAP is used to interpret the importance of variables and understand their impact on predictions [48]. That is, it is a technique based on cooperative game theory that is used to explain the predictions of machine learning models. It aims to assign an importance value to each variable in a prediction, indicating how much each variable contributes to the final outcome of the model.

## IV. Results

Table I presents the performance metrics of the evaluated models. It is observed that the K-Nearest Neighbors (KNN) model obtained the best performance, with an $R^2$ of 0.972 and low errors (RMSE: 507.67, MAE: 479.79, MSE: 2.577), followed closely by Ensemble Bagging, which presents the best performance, with significantly low error values (RMSE, MAE, and MSE) and a coefficient of determination $R^2$ of 0.971 respectively, indicating excellent predictive capacity. The Fine Trees and Decision Tree-Coarse models also shows good performance with $R^2$ of 0.70 and 0.86, respectively. On the contrary, Gaussian Process Regression, Support Vector Machine - Linear, Neural Network, and Random Forest presented poor results, with negative $R^2$ values, which indicates that these models failed to correctly capture the relationship in the data and have poor predictive capacity, as seen in Table I. Therefore, the K-Nearest Neighbors (KNN) model is selected as the best model due to its higher coefficient of determination and better performance in error metrics.

Fig. 1 presents four bar charts comparing the performance of different models using statistical metrics such as RMSE, MAE, MSE, and $R^2$. One specific model is observed to have high RMSE, MAE, and MSE values, indicating that its predictions are highly inaccurate compared to the others. Furthermore, the $R^2$ chart shows a significant negative value, suggesting that the model performs worse than a simple mean of the data. These results highlight the importance of choosing models with lower error and greater explanatory power to ensure more accurate predictions in the analysis of economic growth and fiscal policy in Peru.

TABLE I. Performance Metrics ($R^2$, RMSE, MSE, MAE) of Eight Machine Learning Algorithms in Economic Growth Prediction

| Algorithms | RMSE | MAE | MSE | R2 |
|---|---|---|---|---|
| Gaussian Process Regression | 7112.721647 | 5947.319059 | 5.059081 e+07 | -4.450982 |
| Fine Trees | 1651.050643 | 1244.274174 | 2.725968 e+06 | 0.706287 |
| Random Forest | 640502.801882 | 242370.227261 | 4.102438 e+11 | -44201.331238 |
| Support Vector Machine - Linear | 4494.461921 | 3850.421271 | 2.020019 e+07 | -1.176499 |
| Neural Network | 93653.049841 | 68484.708929 | 8.770894 e+09 | -944.032962 |
| K-Nearest Neighbors | 507.668979 | 479.793237 | 2.577278 e+05 | 0.972231 |
| Ensemble bagging | 514.511294 | 417.417693 | 2.647219 e+05 | 0.971477 |
| Decision Tree-Coarse | 1117.733454 | 884.153401 | 1.249328 e+06 | 0.865389 |

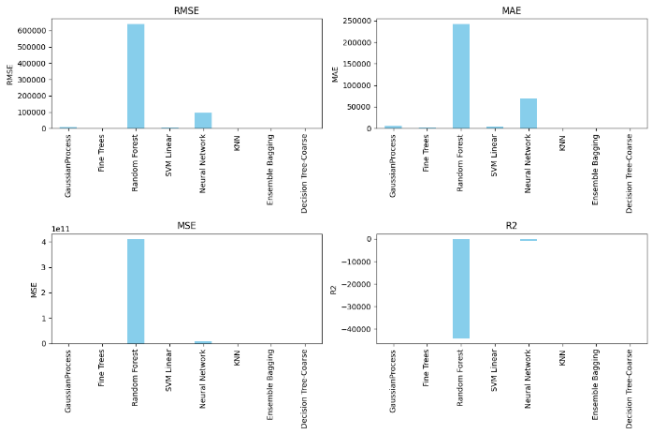


Fig. 1. Evaluating the performance of machine learning models.

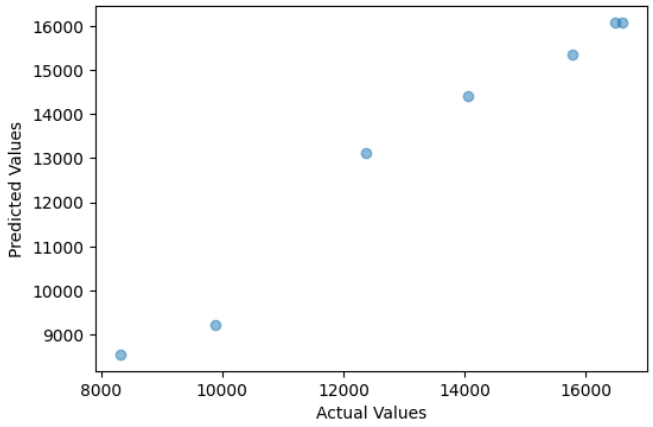


Fig. 2. Comparison of actual and predicted values.

Fig. 2 presents a scatter plot comparing actual values with values predicted by a K-Nearest Neighbors (KNN) model, showing a positive linear relationship where the points cluster around an upward trend, suggesting that as actual values increase, predicted values also increase. Therefore, the model used has a good predictive capability.

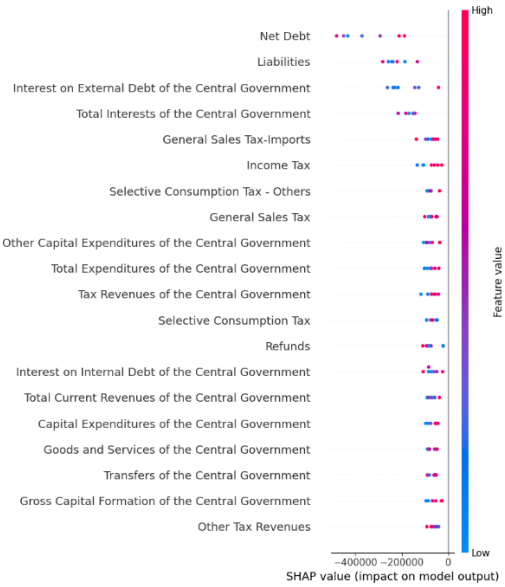


Fig. 3. SHAP Analysis of the importance of variables.

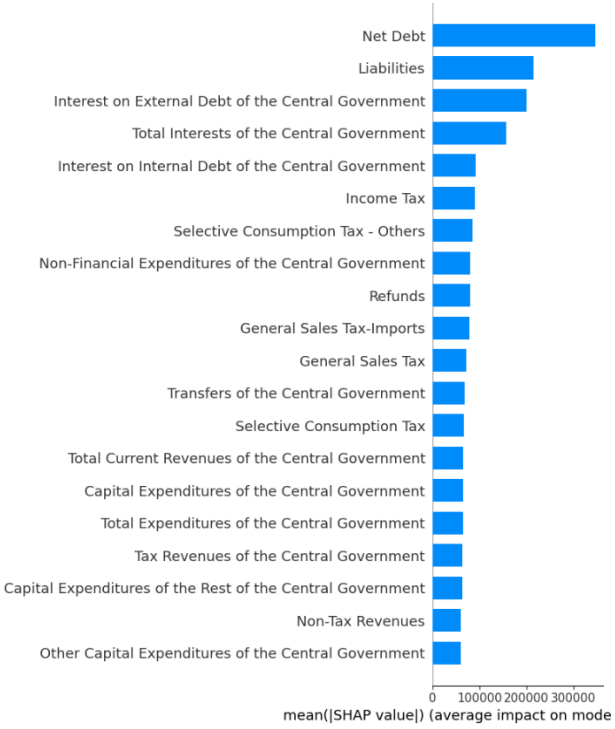


Fig. 4. Average importance of the characteristics according to SHAP values.

The importance of variables in predictive growth models using SHAP values. Fig. 3, shows the greatest influence of a variable on a specific prediction at each point, with colors indicating the characteristic's value (blue for low values and red for high values). Variables such as "Net Debt," "Liabilities," and "Interest on Central Government External Debt" are observed to have an influence on the model's predictions, as they have high SHAP values, indicating their strong contribution to the results. Fig. 4, presents the summary of the average importance of each variable in the model, highlighting again that "Net Debt" and "Liabilities" are the most influential factors. Therefore, these visualizations confirm that variables related to debt and tax revenue play an important role in predicting economic growth, suggesting that policies that affect these indicators can directly impact economic projections.


Fig. 5. Breakdown analysis of the results of fiscal policy variables.

Fig. 5 provides a detailed breakdown of the importance of fiscal policy variables in predicting economic growth outcomes. Similarly, SHAP explains and shows how different variables influence the model's prediction. The prediction base is approximately 2.52 million, but the factors represented in blue have decreased the final prediction to 9,206.99. Public investment has a slight positive influence, while net debt, liabilities, central government interest, income tax, and central government gross capital formation have negative effects on the prediction, suggesting that these factors are associated with a decline in economic growth. This reinforces economic theory, indicating that high levels of debt and tax burden can limit the dynamism of real GDP, highlighting the importance of a balanced fiscal policy in fostering sustainable economic development.

## V. Discussion

The results obtained in this study demonstrate that the K-Nearest Neighbors (KNN) model and Ensemble Bagging are highly effective in predicting Peru's economic growth using fiscal policy variables. In particular, the KNN model achieved a coefficient of determination ($R^2$) of 0.972. These models showed high prediction accuracy, with low errors in the RMSE, MAE, and MSE metrics. Furthermore, the variables with the greatest influence on the prediction, according to SHAP, were Net Debt, Liabilities, and Interest on External Debt, suggesting that these variables play a relevant role in the country's economic dynamics.

Thus, these findings underscore the importance of fiscal policy management for economic growth. Previous studies have highlighted that government debt and fiscal policy can have positive or negative effects depending on their administration [1], [4]. The identification of net debt and liabilities as important variables confirms the importance of prudent public debt management to avoid adverse impacts on the economy. Furthermore, such management is essential for promoting sustainable economic growth in Peru.

It is worth noting that the results are consistent with previous research, such as the usefulness of Machine Learning models in macroeconomic prediction [49]. The superiority of the KNN model over other models, such as Random Forest and Neural Networks, agrees with studies that highlight the effectiveness of models based on economic time series [50]. Furthermore, the application of SHAP for model interpretation reinforces the need for explanatory tools in predictive economics, as they allow results to be more accessible, understandable, and ultimately, more useful for informed and responsible decision-making [51].

Despite the promising results, this study has some limitations. First, the data used come exclusively from the

Central Reserve Bank of Peru, which may limit the generalizability of the findings to other economies with different fiscal policy structures. Furthermore, social or environmental variables, such as income inequality or climate change, which could influence economic growth, were not included [52]. Finally, the study focused on annual data, which may not capture short-term economic dynamics.

Consequently, future research could focus on integrating high-frequency data and incorporating international financial indicators to improve the models' predictive capacity. Likewise, the use of hybrid approaches that combine econometric techniques with deep learning could provide better results in economic prediction [53].

## VI. Conclusion

This study analyzes the application of machine learning models to predict Peru's economic growth using fiscal policy variables with a high degree of accuracy, especially with the KNN and Ensemble Bagging models. These models have proven to be highly effective and robust for economic analysis, as they are able to capture nonlinear relationships between fiscal variables and economic growth, outperforming traditional approaches such as Random Forest and neural networks.

Furthermore, the SHAP analysis identified the most influential variables, providing valuable information for fiscal policy decision-making. In particular, it highlights the importance of Net Debt, Liabilities, and Interest on External Debt as key factors affecting economic growth.

Finally, the K-Nearest Neighbors (KNN) model was selected as the best for its performance and robustness. As a result, the study validates the use of machine learning models for economic forecasting and suggests that prudent fiscal management, focused on debt and liability control, positively influences Peru's economic growth. Furthermore, this work contributes significantly to the field of macroeconomic forecasting.

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# Evaluating User Acceptance and Usability of AR-Based Indoor Navigation in a University Setting: An Empirical Study

Toma Marian-Vladut[1], Turcu Corneliu Octavian[2], Pascu Paul[3]
Computers-Electronics and Automation Department, Stefan Cel Mare University of Suceava, Suceava, Romania[1, 2]
Department of Economics-Economic Informatics and Business Administration, Stefan Cel Mare University of Suceava, Suceava, Romania[3]

***Abstract*—This paper presents the development and usability evaluation of a mobile augmented reality (AR) application designed to support indoor navigation within a higher education setting. The system offers real-time visual and audio guidance without requiring additional infrastructure, leveraging spatial anchors, QR code initialization, and compatibility with both ARCore and ARKit platforms. Users can select destinations such as classrooms, offices, and restrooms, and follow augmented reality overlays to reach them efficiently. A review of existing AR navigation systems highlights current technological approaches and gaps in user-centered research, particularly within academic institutions. Building on these findings, the proposed application was tested in a large-scale empirical study involving 256 students, situated in the context of spatial computing within a university environment. Data collection was based on the System Usability Scale and the Technology Acceptance Model, with four research hypotheses examining ease of use, usefulness, system responsiveness, and continued usage intention. Results revealed significant correlations between intuitive design and usability scores, as well as between perceived usefulness and behavioral intention to reuse the application. These findings reinforce the value of user-centered design in developing infrastructure-free mobile AR systems and demonstrate their potential to improve spatial orientation in complex educational building.**

***Keywords*—Augmented reality; indoor navigation; mobile application; usability evaluation; ARCore; higher education; spatial computing**

## I. Introduction

Indoor navigation continues to pose significant challenges across various public and institutional domains such as healthcare, transportation, and education. Conventional methods—including static signage, printed maps, and directory boards—often prove insufficient in large, unfamiliar, or dynamically changing environments [1]. This is particularly relevant in academic settings, where students and visitors frequently navigate multi-functional and multi-story buildings without prior familiarity.

Augmented Reality (AR) offers promising solutions by superimposing digital content—directional arrows, labels, or information panels—directly onto the user's physical surroundings, thus supporting real-time, intuitive orientation [2]. AR has already demonstrated benefits in outdoor wayfinding, primarily through GPS-based systems [3]. However, GPS signals are typically unavailable indoors, necessitating the use of alternative localization strategies such as Visual Positioning Systems (VPS), Simultaneous Localization and Mapping (SLAM), and visual-inertial odometry [4].

Recent advancements in mobile AR technologies and spatial computing frameworks have enabled the development of indoor navigation systems across various domains, including healthcare, retail, cultural heritage, and education. These systems commonly employ technologies such as WiFi fingerprinting, Bluetooth Low Energy (BLE) beacons, SLAM, or markerless tracking, often in combination with AR platforms like ARKit and ARCore [5]. While promising results have been reported, academic institutions—despite their navigational complexity—remain comparatively underexplored. Moreover, many studies focus on proof-of-concept applications or small-scale usability assessments, highlighting a need for broader empirical validation in dynamic, real-world settings such as university campuses [6].

This paper addresses this gap by presenting the development and evaluation of a mobile AR navigation system designed for indoor use within a university campus building. The application is based on Unity 3D and the ARway SDK and is compatible with ARCore and ARKit, enabling deployment on both Android and iOS platforms without the need for additional infrastructure. The system relies on spatial anchors and camera-based localization initialized via QR code scanning, guiding users through directional AR overlays and audio cues.

The main contribution of this study is twofold: first, it introduces a scalable, infrastructure-free AR application adapted to academic environments; second, it provides a comprehensive empirical evaluation based on a large user study (N = 256), focusing on perceived usability, system responsiveness, and user acceptance. A structured questionnaire derived from the System Usability Scale (SUS) [7] and the Technology Acceptance Model (TAM) [8] was used to test four research hypotheses concerning intuitiveness, perceived usefulness, and behavioral intention to reuse the application.

The findings presented here extend prior work in AR-based indoor navigation and contribute novel insights into mobile AR

usability within educational institutions, with implications for the design of future user-centered navigation systems in complex-built environments.

This paper is organized as follows: Section II provides a review of related work in the field of augmented reality-based indoor navigation, with particular focus on systems implemented in educational settings. Section III presents the research methodology, including system development, participant demographics, and the experimental setup. Section IV discusses the empirical results from the usability evaluation and hypothesis testing. Section V outlines the study's key limitations and their implications. Finally, Section VI concludes the paper by summarizing the main findings and suggesting directions for future research.

By situating this work within the broader landscape of spatial computing and user-centered AR design, the study offers novel insights into the deployment of infrastructure-free navigation systems in higher education. Through one of the largest usability evaluations conducted in a real university setting, the findings provide evidence of how intuitive and responsive AR interfaces can improve indoor orientation and support student navigation experiences in complex buildings.

## II. Related Work

Augmented Reality (AR) technologies have gained increasing attention as powerful tools for facilitating spatial orientation in both outdoor and indoor environments. By superimposing digital information—such as directional cues, contextual data, or visual guides—onto the physical world, AR enhances users' spatial cognition, supports real-time decision-making, and improves the overall navigation experience. While outdoor AR navigation systems have become more mature due to their integration with GPS and digital cartography, indoor navigation presents a distinct set of challenges that demand specialized solutions. Factors such as the absence of GPS signals, complex architectural layouts, and the need for micro-localization accuracy require alternative approaches that leverage visual markers, wireless signal mapping, and sensor fusion. As buildings become increasingly multi-functional and dynamic, effective indoor navigation—especially in public or semi-public spaces like airports, hospitals, and university campuses—has become not only desirable, but essential.

This literature review focuses specifically on AR navigation systems designed for indoor environments. By examining a range of implementations, empirical evaluations, and technological strategies, the review identifies trends, challenges, and gaps in the field. The ultimate aim is to contextualize and inform the development and testing of a mobile AR application tailored to indoor navigation within a university building—a scenario that combines both technical complexity and high user variability.

While foundational models such as Spatial Cognition Theory [9] and Situated Learning Theory [10] provide historical context, more recent research has emphasized practical and user-centered approaches for mobile AR navigation in educational settings. Bermejo et al. [11], offer a broad overview of AR applications in learning environments, while Zulfiqar et al. [12], identify both the usability benefits and implementation challenges of AR tools. These perspectives align with the increasing emphasis on mobile HCI, accessibility, and real-world deployment in university contexts.

Contemporary implementations often rely on more recent human-centered design principles and empirical HCI models [13]. Recent studies demonstrate diverse combinations of technologies and contexts: BLE beacons, SLAM, visual-inertial odometry, tactile and audio feedback, and ARCore/ARKit platforms. Use cases range from libraries and office buildings to hospitals, museums, and airports. Notably, several studies focus on accessibility and inclusive design, such as those by Mishra et al. [15] and Jain & Singh [16], while others explore high-accuracy solutions for complex layouts in university and medical facilities [17], [18].

Recent empirical studies have continued to explore the impact of AR on spatial understanding and usability in complex indoor environments. Cheng and Tsai [19] conducted a meta-analysis on the effectiveness of AR in supporting orientation and task efficiency, confirming its benefits in unfamiliar environments like educational campuses. Similarly, Bacca et al. [20] reviewed AR applications in higher education, underscoring the importance of multimodal feedback and responsive interaction design in user navigation experiences.

To summarize these findings, TABLE I. presents a comparative overview of recent and relevant AR systems developed specifically for indoor navigation. The table highlights each system's technological stack, target environment, study design, key findings, and limitations. This focused comparison offers a consolidated view of the current landscape and provides a reference point for the development of the proposed application.

A closer examination of Table I, reveals several trends and research directions. First, BLE beacons, SLAM, and markerless AR remain among the most frequently implemented technologies, often combined with ARCore or ARKit for rendering and interface management. Use cases involving hospitals, libraries, and museums prioritize accessibility and user comfort, while high-precision systems for transportation hubs and campuses aim at efficiency and scalability. University-focused systems are increasing in number, but still underrepresented, creating an opportunity for further research in this domain. Although many applications show high satisfaction and orientation success rates, challenges such as occlusion, signal reliability, infrastructure requirements, and energy consumption persist.

Building upon this landscape, the present research introduces and evaluates a mobile AR application designed to support indoor navigation within a university campus building. The system integrates inertial sensors and spatial anchors to generate real-time directional overlays, assisting users in locating academic spaces such as classrooms, administrative offices, restrooms, and exits. The design emphasizes usability, speed of response, and intuitive interaction, with the goal of supporting both first-time visitors and regular users of the building.

TABLE I. COMPARATIVE ANALYSIS OF RECENT INDOOR AR NAVIGATION SYSTEMS

| Study | Environment | Technologies Used | Participants | Key Results | Limitations |
|---|---|---|---|---|---|
| Rossi et al. [14] | Office building | Visual markers, ARKit | 30 | 35% reduction in wayfinding time | Requires precise marker placement |
| Nguyen & Park [5] | Shopping mall | Bluetooth beacons, AR overlays | 25 | 82% accuracy in navigation | Signal interference in crowded areas |
| Gupta et al. [4] | Hospital | WiFi fingerprinting, SLAM | 35 | 78% room-finding success rate | High computational demands |
| Mishra et al. [15] | Simulated indoor | Sonar sensors, audio AR | 20 | 90% obstacle avoidance for visually impaired | Latency in real-time audio processing |
| Jain & Singh [16] | Public library | Tactile feedback, AR overlays | 15 | 85% satisfaction for mobility-impaired users | Battery drain during prolonged use |
| Chen et al. [17] | University campus | ARCore, visual-inertial odometry | 50 | 81% ease-of-use rating, strong multi-floor support | Learning curve for first-time users |
| Ahn et al. [18] | Medical facility | LIDAR, SLAM, semantic mapping | 40 | 86% orientation success, cognitive load reduced | LIDAR dependency, limited mobile support |
| Sato et al. [21] | Museum | Markerless AR, cloud anchors | 32 | 77% task completion, high engagement | Occlusion issues in high-traffic zones |
| Yamamoto et al. [6] | University building | BLE beacons, 3D AR navigation | 50 | 72% satisfaction, effective in complex layouts | Limited beacon range across floors |
| Zhao et al. [22] | Conference center | UWB + AR headset | 28 | 88% task success rate, sub-meter precision | High setup cost, headset fatigue |
| Lee et al. [23] | Airport terminal | 5G positioning + AR glasses | 45 | 84% accuracy in terminal routing | Infrastructure dependence on 5G |
| Fernandez et al. [24] | Large campus | ARCloud + indoor GPS emulation | 60 | 89% efficiency in route following | Data synchronization delays |
| Watanabe et al. [25] | University library | Computer vision + semantic room tagging | 33 | 80% accuracy in identifying room categories | Tag recognition fails in dim lighting |

## III. METHODOLOGY

### A. Research Design and Context

This study follows an applied, exploratory and user-centered design methodology, combining software development with empirical evaluation. The methodological approach integrates a twofold focus: 1) the design and implementation of a functional AR indoor navigation application, and 2) its validation through structured user testing and statistical analysis.

To structure the evaluation process, two established theoretical frameworks were adopted: the System Usability Scale (SUS) and the Technology Acceptance Model (TAM). These models informed the development of the user questionnaire and the formulation of four research hypotheses, which investigate the relationships between ease of use, system responsiveness, perceived usefulness, and behavioral intention to continue using the application.

The empirical investigation was conducted in a real-world setting—a university campus building—where 256 students participated in testing the application under authentic usage conditions. Their responses were collected immediately after the navigation task was completed.

### B. Description of the AR Navigation Application

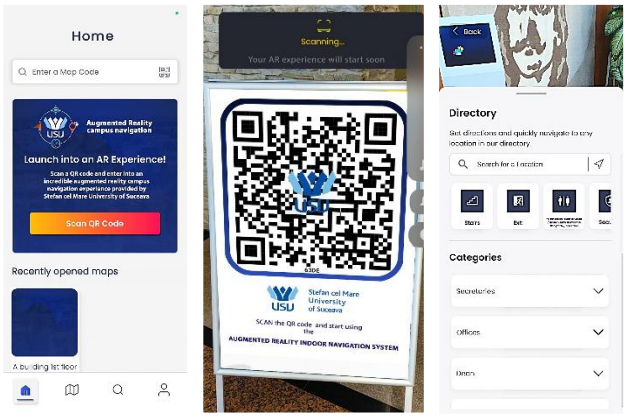
To address the need for effective indoor navigation in academic environments, a mobile augmented reality (AR) application was developed and deployed in one of the university buildings selected as the testing site. The building was instrumented with multiple QR codes positioned both at entry points and at intermediate locations throughout the interior. These QR anchors served not only as access points to initialize spatial localization, but also as recharge points to correct accumulated drift during extended navigation. This design consideration was particularly important given the spatial complexity and scale of a typical campus building, ensuring reliable positioning across the entire route. The application was specifically designed to assist students, staff, and visitors in locating rooms and key functional areas (e.g., classrooms, offices, restrooms) in a fast and intuitive manner, using augmented visual cues superimposed on the physical environment.

*1) Technical foundation and compatibility:* The system was implemented using Unity 3D as the development platform and ARway SDK, a spatial computing solution that supports real-time mapping and localization without the need for additional physical infrastructure such as Bluetooth beacons or RFID tags. The application leverages Simultaneous Localization and Mapping (SLAM) and Visual Positioning System (VPS) technologies to ensure robust tracking and localization accuracy.

For compatibility, the application supports both Android and iOS devices via ARCore and ARKit, respectively. The solution was optimized to run on standard consumer smartphones, minimizing hardware requirements and maximizing accessibility for users.

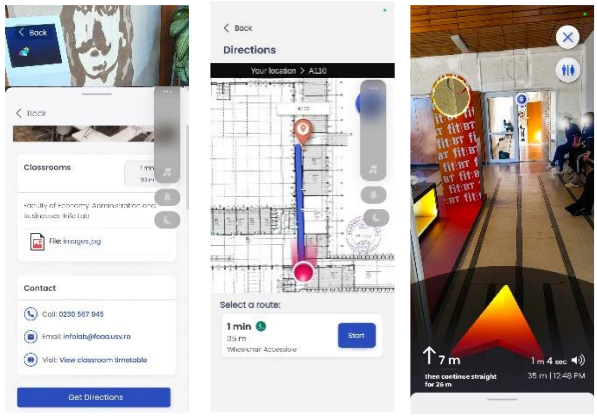
*2) Interaction workflow:* Navigation begins by opening the application (Fig. 1(a)) and scanning a QR code positioned at the entrance of the building (Fig. 1(b)). This initializes the positioning using spatial anchors and loads the AR environment, placing the user within the building's spatial model. From the location directory (Fig. 1(c)), the user can select a destination from a categorized list including:

- Teaching spaces (lecture halls, classrooms),
- Administrative services (secretariats, offices),
- Facilities (restrooms, common areas),
- Informational points (exhibition rooms, noticeboards).




(a) Main interface. (b) QR Code scanning. (c) Destinations.

Fig. 1. User interface and interaction.




(a) Location details. (b) Location path. (c) Overlaying directions.

Fig. 2. User interface and interaction.

Upon selection and pressing "*Get Directions*" (Fig. 2(a)), the system generates a custom navigation path from the user's current position to the target location (Fig. 2(b)). The path is rendered as a series of directional arrows overlaid on the real environment, updated dynamically as the user advances (Fig. 2(c)). Supplementary features include:

- Audio instructions, synchronized with the visual arrows, offering step-by-step guidance.
- Estimated time and distance, displayed in real time on screen.
- Informational panels, which provide context-sensitive data about destinations (e.g. office hours, room capacity).

The application interface was developed with a strong emphasis on usability and clarity. Buttons are large and spaced appropriately, icons are intuitive, and visual contrast ensures legibility in different lighting conditions.

*3) Design considerations and rationale:* A key goal in the application design was to reduce cognitive load and promote spatial awareness through AR-enhanced cues. By eliminating reliance on static maps and textual instructions, the application offers a direct and context-sensitive wayfinding experience. In addition, by not requiring external hardware or server-side connectivity for navigation, the system provides a scalable and self-contained solution—particularly important for dynamic environments like university campuses, where, infrastructure may vary and user populations shift frequently.

### C. Participant Profile and Study Duration

The empirical evaluation of the AR navigation application involved 256 student participants from Stefan cel Mare University of Suceava, Romania. The vast majority were enrolled in the first (70.7%) and second year (26.2%) of undergraduate study, representing typical users who are less familiar with campus infrastructure and more likely to benefit from orientation support. The remaining participants (3.1%) were from other academic levels, including later undergraduate years and Master's programs.

The study was conducted over a period of two weeks in May 2024, during which students were invited to participate in on-site navigation tests. Out of the total participants, 153 reported having previously used augmented reality applications, while the remaining 103 had no prior experience with AR technologies. This contrast provided a useful dimension in evaluating both usability and adoption potential across different user backgrounds.

### D. Experimental Setup and Testing Procedure

To ensure consistency and control across all testing sessions, each participant was required to follow the same predefined navigation route within the selected university building. The target location was intentionally chosen from among less frequently accessed rooms, in order to minimize the likelihood that participants—particularly first-year students—were already familiar with the space. This design choice allowed for a more accurate and unbiased assessment of the application's effectiveness in supporting indoor wayfinding.

Participants began the navigation and followed the application's visual and audio cues to reach the assigned destination. The uniformity of the route across all sessions ensured consistent conditions for evaluating task performance and usability perceptions. After completing the task, participants filled out a structured questionnaire in Google Forms that included items from both the System Usability Scale (SUS) and the Technology Acceptance Model (TAM), targeting key dimensions such as intuitiveness, usefulness, system responsiveness, and behavioral intention to reuse the application.

The complete testing session lasted approximately 10 minutes, including both the navigation interaction and the post task survey. No assistance was offered during the task execution, in order to simulate independent and realistic usage of the application.

### E. Research Hypotheses

The hypotheses formulated for this study are as follows:

- Hypothesis 1: Intuitiveness and Usability Correlation.
- Hypothesis 2: Difficulty with Traditional Orientation and Perceived Usefulness.
- Hypothesis 3: Interface Responsiveness and Usability Perception.
- Hypothesis 4: Perceived Usefulness and Continued Use Intention.

The study was approved by the institutional ethics committee of Ștefan cel Mare University of Suceava. All participants were informed about the purpose of the research and their rights prior to participation. Informed consent was obtained from all individuals, and data collection procedures adhered to institutional guidelines on privacy and ethical research conduct. No personally identifiable information was collected or stored during the study.

In order to validate these hypotheses and assess the system's effectiveness, the results of the empirical testing are analyzed and interpreted in the next section.

## IV. Results

### A. Hypothesis 1 (H1): There is a Statistically Significant Positive Correlation Between the Users' Perception of the Application's Intuitiveness and their Scores on the System Usability Scale (SUS)

This hypothesis explored the relationship between how intuitive users found the application and their overall usability ratings, based on the SUS framework. Intuitiveness is a central construct in both user-centered design and the Technology Acceptance Model (TAM), which posit that ease of use directly influences technology adoption.

To test this, a correlation analysis was conducted between two items: "I found the application easy to use" (measuring intuitiveness), and the final SUS score (scaled to 100). Descriptive statistics are presented in Table II, showing a high mean SUS score (M = 96.86, SD = 14.27) and a favorable ease-of-use perception (M = 3.99, SD = 0.95).

TABLE II. Descriptive Statistics for SUS Score and Perceived Ease of Use

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| **SUS Score (Final)** | 96.86 | 14.27 | 256 |
| **I found the application easy to use** | 3.99 | 0.95 | 256 |

A statistically significant, moderate-to-strong positive correlation was found between the two variables (Pearson's $r = 0.633$, Spearman's $\rho = 0.635$; $p < 0.001$), as shown in Table III.

TABLE III. Correlation Between SUS Score and Perceived Ease of Use (N = 256)

| Variable Pair | Pearson r | Spearman ρ | Sig. (2-tailed) |
|---|---|---|---|
| **SUS Score × Ease of Use Perception** | 0.633 | 0.635 | < 0.001 |

Note: Both correlations are significant at the 0.01 level (2-tailed).

These results support the hypothesis, reinforcing that perceived intuitiveness plays a critical role in shaping usability judgments. As shown in Fig. 3, higher ease-of-use ratings consistently aligned with elevated SUS scores, emphasizing the importance of interface design in enhancing user experience.

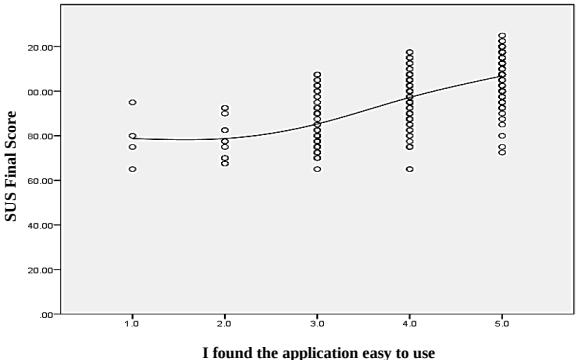



Fig. 3. Analysis of the relationship between users' perceptions of the application's usability and their familiarity with indoor environments.

### B. Hypothesis 2: Indoor Navigation Applications are Perceived as much more Useful by users who Face Difficulties in Traditional Orientation

This hypothesis explored whether participants with lower familiarity navigating campus buildings would find the AR application more useful. The Technology Acceptance Model (TAM) suggests that perceived usefulness is a critical factor influencing technology adoption, particularly in an unfamiliar or complex environments.

To evaluate this relationship, a correlation analysis was conducted using two self-reported Likert-scale items:

- "How well do you know the buildings/rooms on campus (inside)?" (measuring spatial familiarity)
- "I believe that this application significantly improves my ability to navigate inside campus buildings." (perceived usefulness).

Descriptive statistics for both items are presented in Table IV, indicating moderate familiarity with campus buildings and a generally high perception of the application's utility.

TABLE IV. Descriptive Statistics for Navigation Familiarity and Perceived Usefulness

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| **Familiarity with campus buildings** | 3.195 | 0.9037 | 256 |
| **Perceived improvement in indoor navigation** | 4.059 | 0.8168 | 256 |

Pearson and Spearman correlation analyses revealed a strong and statistically significant inverse relationship ($r = -0.866$, $\rho = -0.886$; $p < 0.001$), as shown in Table V. This suggests that users who were less familiar with the campus environment rated the application as significantly more useful.

As visualized in Fig. 4, users with lower spatial familiarity consistently reported higher perceived usefulness of the AR application. These findings confirm the hypothesis and

highlight the potential value of indoor navigation technologies for novice users or those navigating complex built environments such as university campuses.

TABLE V. CORRELATION BETWEEN FAMILIARITY WITH CAMPUS BUILDINGS AND PERCEIVED USEFULNESS (N = 256)

| Variable Pair | Pearson r | Spearman ρ | Sig. (2-tailed) |
|---|---|---|---|
| **Familiarity × Perceived Usefulness** | 0.866 | 0.886 | < 0.001 |

Note: Both correlations are significant at the 0.01 level (2-tailed).

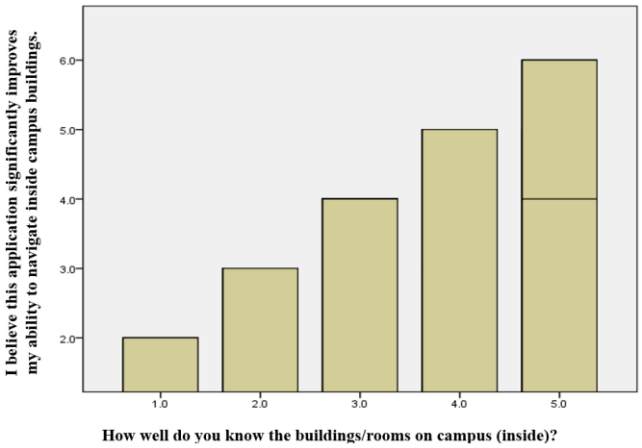



Fig. 4. Cluster analysis of familiarity with campus buildings and perceived utility of indoor navigation app.

This trend suggests an inversely proportional relationship between prior familiarity with the physical environment and perception of the application's utility. Thus, the results support the hypothesis that indoor navigation applications are perceived as more useful by users who experience difficulties in traditional orientation. These results confirm the hypothesis and support the idea that indoor orientation applications can provide real added value, especially in the context of novice users or in complex environments where traditional orientation is difficult.

### C. Hypothesis 3: An Intuitive Interface and a Quick Response Time of the Application Improve the Perception of its Usability

This hypothesis investigated whether interface intuitiveness and AR content responsiveness influence perceived usability, as measured by the System Usability Scale (SUS). According to user experience principles and the Technology Acceptance Model (TAM), both cognitive simplicity and system performance are key drivers of user satisfaction.

Participants rated two statements on a five-point Likert scale:

- "How intuitive did you find the indoor navigation mode?"
- "How quickly was the AR content (VPS, SLAM) loaded and displayed indoors?"

A multiple linear regression was conducted to determine how these two predictors affected the SUS score. The regression model was statistically significant, $F(2, 253) = 40.22$, $p < 0.001$, accounting for approximately 24.1% of the variance in perceived usability ($R^2 = 0.241$), as shown in Table VI.

TABLE VI. MODEL SUMMARY FOR PREDICTING SUS SCORE

| Model | R | $R^2$ | Adjusted $R^2$ | Std. Error of the Estimate |
|---|---|---|---|---|
| **1** | 0.491 | 0.241 | 0.235 | 12.874 |

Both predictors contributed significantly to the model (see Table VII and Table VIII). Response speed of AR content had a stronger effect ($\beta = 0.333$, $p < 0.001$) compared to intuitiveness ($\beta = 0.230$, $p < 0.001$), suggesting that performance responsiveness plays a slightly greater role in shaping usability judgments.

TABLE VII. ANOVA RESULTS FOR SUS REGRESSION MODEL

| Source | Sum of Squares | df | Mean Square | F (Sig.) |
|---|---|---|---|---|
| **Regression** | 13333.365 | 2 | 6666.683 | 40.221 (p < 0.001) |
| **Residual** | 41934.994 | 253 | 165.751 | |
| **Total** | 55268.359 | 255 | | |

TABLE VIII. REGRESSION COEFFICIENTS FOR PREDICTORS OF SUS SCORE

| Predictor | Unstandardized B | Std. Error | Standardized Beta | Sig. |
|---|---|---|---|---|
| **Constant** | 62.662 | 4.075 | - | < 0.001 |
| **Loading speed (AR content)** | 5.887 | 1.120 | 0.333 | < 0.001 |
| **Intuitiveness** | 3.492 | 0.961 | 0.230 | < 0.001 |

As illustrated in Fig. 5, higher SUS scores were associated with more favorable ratings of both interface intuitiveness and AR responsiveness. These results support the hypothesis and underscore the importance of optimizing both design clarity and performance speed in mobile AR navigation systems.

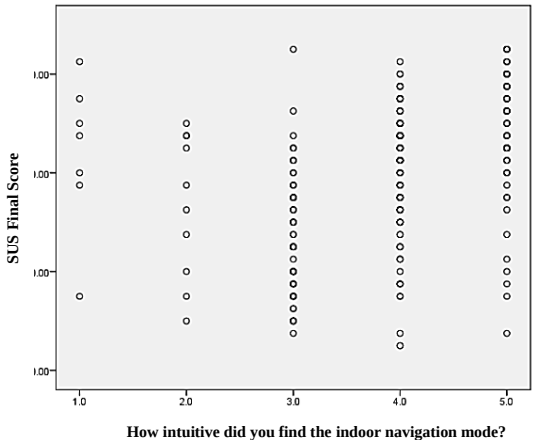



Fig. 5. Relationship between intuitiveness of indoor navigation module and System Usability Scale (SUS) Scores.

### D. Hypothesis 4: The Perception of the Application's Utility Influences the Intention to use it Regularly

This hypothesis evaluated whether users who perceived the application as useful also expressed a stronger intention to continue using it in the future. In line with the Technology

Acceptance Model (TAM), perceived usefulness is a central determinant of behavioral intention and long-term adoption.

Participants responded to two Likert-scale statements:

- "I believe that this application significantly improves my ability to navigate inside campus buildings." (perceived usefulness).
- "I would be willing to use this application regularly for indoor navigation on campus." (intention to reuse).

Descriptive statistics for both variables are presented in Table IX, showing consistently high ratings for both perceived usefulness (M = 4.059) and reuse intention (M = 4.027).

TABLE IX. DESCRIPTIVE STATISTICS FOR PERCEIVED USEFULNESS AND BEHAVIORAL INTENTION

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| **Perceived Usefulness** | 4.059 | 0.8168 | 256 |
| **Intention to Reuse** | 4.027 | 0.8698 | 256 |

A strong and statistically significant positive correlation was found between the two items (Pearson's r = 0.761, Spearman's ρ = 0.780; $p < 0.001$), as shown in Table X.

TABLE X. CORRELATION BETWEEN PERCEIVED USEFULNESS AND INTENTION TO REUSE (N = 256)

| Variable Pair | Pearson r | Spearman ρ | Sig. (2-tailed) |
|---|---|---|---|
| **Usefulness × Intention to Reuse** | 0.761 | 0.780 | < 0.001 |

Note: Both correlations are significant at the 0.01 level (2-tailed).

These findings confirm the hypothesis and align with TAM's core assertion that usefulness directly predicts usage behavior. As visualized in Fig. 6, participants who strongly agreed with the application's utility also expressed a higher willingness to use it regularly. This suggests that future AR navigation systems should prioritize tangible user value—such as improved spatial orientation and task efficiency—to support sustained adoption.

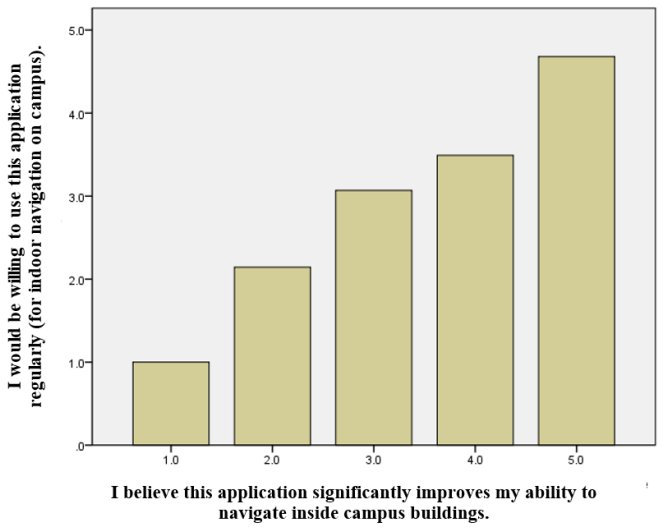



Fig. 6. Conceptual relationship between perceived usefulness and behavioral intention to reuse, based on TAM.

## V. LIMITATIONS

While the study provides valuable insights into the usability and user acceptance of an AR-based indoor navigation system in a university setting, several limitations should be acknowledged. First, the navigation system was tested within a single academic building, which may limit the generalizability of the results to other campus environments with different layouts or levels of complexity. Second, the participant sample consisted primarily of first and second-year undergraduate students, a group that may be more receptive to mobile technologies and less representative of the broader university population, including faculty, staff, or postgraduate students.

Third, the evaluation was based on short-term use, focusing on first-time interactions with the application. Long-term usage patterns, user fatigue, and sustained engagement were not explored and remain areas for future research. Finally, environmental factors such as lighting conditions, device performance variability, and accessibility needs were not systematically tested, although they may significantly impact AR experience quality in real-world use.

Addressing these limitations in future studies—through multi-building deployment, broader demographic sampling, and longitudinal testing—could enhance the robustness and applicability of the findings.

## VI. CONCLUSION

This study presented the development and evaluation of a mobile augmented reality (AR) navigation system designed for indoor use in an academic environment. Built using Unity and the ARway SDK, the application enables infrastructure-free indoor guidance through visual and auditory cues, anchored via QR codes and spatial localization.

- A large-scale empirical evaluation involving 256 participants demonstrated the application's effectiveness and strong user acceptance. The results offer robust support for all four research hypotheses.
- Users who perceived the application as intuitive and responsive reported significantly higher SUS scores.
- Those with limited prior knowledge of campus interiors rated the system as more useful.
- A strong correlation was found between perceived usefulness and the intention to reuse the application.

These findings, supported by statistically significant correlations and regression models confirm the importance of interface intuitiveness, performance responsiveness, and contextual relevance in shaping AR usability and adoption.

By focusing on a real-world academic scenario and validating the system across a substantial and demographically relevant sample, the study contributes both methodologically and practically. It offers empirical grounding for future AR systems targeting orientation in unfamiliar environments, particularly for students and first-time visitors.

In summary, the study demonstrates that scalable AR indoor navigation systems can meaningfully improve spatial orientation, particularly for novice users. Future directions

include expanding to hybrid indoor–outdoor scenarios, integrating dynamic real-time data, and supporting inclusive design through multimodal interaction modalities such as voice guidance and haptic feedback.

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# A Hybrid Length-Based Pattern Matching Algorithm for Text Searching

Victor Cornejo-Aparicio, Cesar Cuarite-Silva, Antoni Benavente-Mayta, Karim Guevara
Universidad Nacional De San Agustín De Arequipa, Arequipa, Perú

***Abstract*—This paper presents a hybrid algorithm for pattern matching in text, which combines word length preprocessing with the Knuth-Morris-Pratt (KMP) algorithm. Its performance was evaluated against KMP and Boyer-Moore (BM) in two scenarios: synthetic texts and real-world texts. In the former, classical algorithms proved more efficient due to the uniform structure of the data. However, in real-world texts, the hybrid algorithm significantly reduced search times, thanks to its ability to filter matches by length patterns before performing character-by-character comparisons. The algorithm also demonstrated flexibility in recognizing patterns with different delimiters. Among its limitations is the difficulty in detecting substrings within longer words. As future work, the incorporation of partial matching techniques and the adaptation of the approach to multilingual environments and machine learning systems are proposed. The dataset used is provided to encourage reproducibility.**

***Keywords*—*Knuth-Morris-Pratt; Boyer-Moore; text search; hybrid algorithm, preprocessing; word-length patterns; test text for experiments***

## I. Introduction

In the field of text processing and pattern matching, algorithmic efficiency is a crucial factor for numerous applications, particularly in the search for substrings within large volumes of data. This need becomes even more relevant in areas such as data mining, information retrieval, and text analysis, where fast, accurate, and scalable search mechanisms are required.

Classical algorithms such as Knuth-Morris-Pratt (KMP) and Boyer-Moore (BM) have been widely used due to their proven mathematical efficiency. However, these algorithms exhibit limitations in certain scenarios, such as datasets with high repetitiveness or large and unbalanced alphabets. Under these conditions, their performance tends to degrade, increasing computational overhead and reducing the overall efficiency of the system.

In response to these challenges, the objective of this work is to reduce the time required to locate strings within large texts through an alternative approach that leverages the internal structure of natural language. To this end, we propose a novel substring search method based on word length patterns, which enables the use of a more compact and structured representation of the original text as the basis for searches.

The proposed solution introduces a hybrid algorithm that combines a preprocessing step—in which the sequence of word lengths is extracted—with the traditional KMP algorithm. In this way, a preliminary search is conducted on a reduced representation of the text (based on word lengths), and full validation is performed on the original content only when potential matches are detected. This strategy accelerates the pattern location process and enhances the overall performance of the algorithm.

Thus, the present research addresses a practical need in the processing of large volumes of text by proposing a method that exploits the structural properties of language to improve the speed and efficiency of searches.

The remainder of this paper is organized as follows: Section II presents related work. Section III provides a review of the relevant literature. Section IV details the proposed algorithm. Section V offers a comparative analysis of the complexity of the algorithms considered. Section VI presents the experimental results. Section VII is devoted to discussing the results, including key observations, identified limitations, and mitigation strategies. Section VIII summarizes the study's conclusions, and finally, Section IX outlines possible future directions aimed at refining the hybrid algorithm.

## II. Related Works

Over the years, several studies have proposed new hybrid and compression-based approaches aimed at reducing the number of comparisons and improving the efficiency of string search, making them highly effective for large-scale applications.

SSTBMQS [1] is a hybrid algorithm that combines the best features of two existing algorithms: Tuned Boyer-Moore [2] and Quick-Skip Search [3]. Its results demonstrate superior performance in reducing character comparison attempts.

The hybrid Quick-Skip Search algorithm [3] seeks to optimize exact string matching by combining techniques from the Quick Search and Skip Search algorithms. The goal is to minimize the number of character comparisons and enhance search speed in large text volumes.

AbuSafiya [4] proposes accelerating text search in natural language through data compression. A fast compression algorithm was designed to encode each character using a single byte, thereby reducing text size and speeding up the search process. Although this technique is limited to texts in a single language, experimental results showed a significant reduction in search time.

## III. Literature Review

### A. Brute Force Search Algorithm

The brute force string search algorithm is one of the simplest methods for finding a substring within a larger text. It works by

comparing the target pattern with every possible substring of the text, starting from the first character and moving sequentially to the end. While its implementation is straightforward, its efficiency is low, with a worst-case time complexity of O(n * m), where, n is the length of the text and m is the length of the pattern [5]

### B. Knuth-Morris-Pratt Algorithm

The Knuth-Morris-Pratt (KMP) algorithm was developed by Donald Knuth, James H. Morris, and Vaughan Pratt in 1977 [6], [7]. It builds a failure table that stores information about the prefixes and suffixes of the pattern. This table allows the algorithm to determine the optimal shift when a mismatch occurs.

Although the algorithm achieves linear time complexity in the worst case, its implementation can be complex, and it may underperform compared to other algorithms in practice [8].

KMP improves pattern matching by avoiding unnecessary comparisons. It uses a shift table to skip characters when a mismatch is found, relying on previous match information. Its time complexity is O(n + m), making it significantly more efficient than brute force search, especially in long texts [9].

### C. Boyer-Moore Algorithm

The Boyer-Moore algorithm, developed by Robert S. Boyer and J. Strother Moore in 1977 [10], [11], is among the most efficient techniques for pattern searching in text strings. It compares the pattern to the text from right to left, enabling significant skips that optimize the search process. It performs particularly well on long texts and when the pattern contains infrequent characters.

In worst-case scenarios, such as when the pattern and text have many similarities or frequent characters are in unfavorable positions, its time complexity can reach O(n * m), where n is the length of the text and m is the length of the pattern.

Boyer-Moore employs two heuristics—the bad character rule and the good suffix rule—to skip over portions of the text that have already been examined. In the best case, it can achieve a time complexity of O(n/m), making it extremely fast for large-scale text processing [5].

### D. Rabin-Karp Algorithm

The Rabin-Karp algorithm uses a hashing technique for pattern matching. Instead of performing direct comparisons, it computes a hash value for the pattern and for each window of the text, and checks for matches based on these hash values. While the average-case performance is O(n + m), it can degrade in the worst case due to hash collisions, especially when many substrings produce the same hash value [7], [12].

### E. Aho-Corasick Algorithm

The Aho-Corasick algorithm is an efficient method for searching multiple patterns in a text simultaneously. It constructs a finite automaton that allows the simultaneous search of all patterns. During its preprocessing phase, it builds a trie (prefix tree) of the patterns, enhanced with failure pointers that manage mismatches efficiently. The algorithm runs in O(n + z + m) time, where, n is the length of the text, z is the total number of pattern occurrences found, and m is the sum of the lengths of all patterns. This makes it a robust solution for applications involving the search of multiple strings within large datasets [13].

## IV. Proposed Algorithm

The proposed algorithm comprises two main components: a preprocessing phase using a length-pattern-based algorithm and a hybrid algorithm that, leveraging the preprocessing results, executes the final search for the specified pattern within the text.

### A. Algorithm Based on Length Pattern (LP)

In order to design the algorithm, the following premises must first be considered

Premise 1: Texts contain information, which is represented through words, numbers, and certain symbols. These elements will be referred to as the information body, as they constitute the relevant content that needs to be located.

Premise 2: Each element of the information body has a specific length, and when combined to form information, they generate structural patterns that can be identified. Therefore, these patterns can be located within the text by analyzing the lengths of their components.

Premise 3: The substrings that form the information body are composed of sequences (words or numerical values) separated by whitespace or other non-informative characters (such as punctuation marks). When observing the text as a whole, it becomes evident that the informative sequences are delimited by non-informative ones, which enables the structure to be distinguished through length-based analysis.

In this context, both the original texts and the search patterns contain information represented by words, numbers, and symbols. All of these are processed through a preprocessing phase aimed at determining the individual length of each informative substring. Based on this information, a reduced representation of the original text is constructed—referred to as the pattern of lengths—as illustrated in Fig. 1.

In the preprocessing stage it is necessary to determine the “Function Include” in which the characters conforming the body of information are discriminated. Thus, the lengths of the information strings and those that do not constitute information are maintained.

**Algorithm 1:** Function Include

```
Include (character)
    alphaNum = ^[a-zA-Z0-9]
    inclusion = (character is in alphaNum)
    return (inclusion)
End
```

Based on the inclusion function, it is deduced that if a pair of terms that constitute information are separated by a character not included in 'String', such as punctuation marks, hyphens, or others, the algorithm will be able to identify them correctly. This is the case, for example, with the terms 'pre-processar' and 'pre processar', which, when subjected to preprocessing, produce the same result in terms of length pattern.

| Position | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Text | H | E | L | L | O | | F | R | I | E | N | D | S | , | | H | O | W | | A | R | E | | Y | O | U | ? |
| Word Length | 1 | 2 | 3 | 4 | 5 | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | | | 1 | 2 | 3 | | 1 | 2 | 3 | | 1 | 2 | 3 | |

| Pre-Processing Text | 0 | 5 | 0 | 7 | 0 | 3 | 0 | 3 | 0 | 3 | 0 |
|---|---|---|---|---|---|---|---|---|---|---|---|

Position Vector {0,6,15,19,23}

| Position | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| Pattern | H | O | W | | A | R | E |
| Word Length | 1 | 2 | 3 | | 1 | 2 | 3 |

| Pre-Processing Pattern | 0 | 3 | 0 | 3 |
|---|---|---|---|---|

Fig. 1. Preprocessing example.

Once the original text is available, and in which the search target text is to be found, the development of the search algorithm mechanism based on the length pattern (LP) proceeds as shown graphically in (Fig. 2).

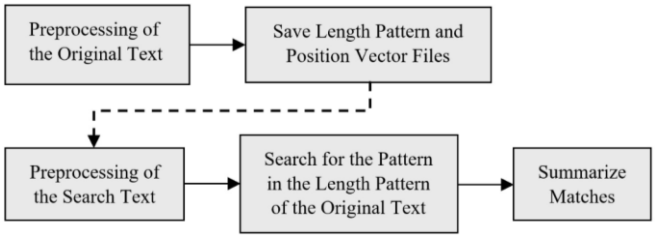


Fig. 2. Search sequence using the LP algorithm .

During the preprocessing of the original file—an initial stage of the algorithm—two text files must be generated simultaneously. The first file contains the pattern of word lengths, while the second stores a vector with the starting positions of each word that holds information. The pseudocode entitled “Preprocessor” presents the sequence of the algorithm based on the Pattern of Lengths (PL).

**Algorithm 2:** Preprocessor

```
Preprocessor(text):
    set txtInf = "", txtSep = "", txtIndexes = ""
    set inSep = false, inInf = false
    set x = 0, y = 0, indexAcc = 0, acc = 0
    For (char in text)
        If (char is alphanumeric) then
            If (inSep) then
                txtSep += formatToString(y, 2)
                y = 0, inSep = false
                acc += y
                indexAcc++
            End
            x++, inInf = true
        Else
            If (inInf) then
                txtInf += formatToString(x, 2)
                x = 0, inInf = false
                acc += x
                indexAcc++
            End
            y++, inSep = true
        End
        If (indexAcc == 2) then
            txtIndexes += acc
            acc = 0
        End
    End
    saveFile(txtInf, "txtLengths.inf")
    saveFile(txtIndexes, "txtIndexes.ind")
    Return 0
End
```

### *B. Hybrid Algorithm Based on LP and KMP (LP-KMP)*

Once both the original text and the search pattern have been preprocessed, the word length patterns corresponding to each word in both texts are obtained. These patterns, extracted as text from the files generated during preprocessing, are used as input data for the KMP algorithm with the objective of locating the positions where the sequences of word lengths in the text and the pattern match. The identified match positions are stored in an index vector.

Subsequently, the actual positions in the original text are retrieved using the previously generated position vector. At these locations, a character-by-character comparison is performed between the corresponding text substring and the full search pattern. If all characters match, a valid match is confirmed. The pseudocode labeled “Hybrid” presents the complete sequence of the PL-KMP hybrid algorithm.

**Algorithm 3:** Hybrid

```
Hybrid (text, pattern, lengthsTxt, lengthsPatt, indexes):
    set posMatched = 0, indFirstWord = 0
    set sizePattWords = lengthsPatt.size()
    set wordsPatt = sizePattWords/2
    set countPatternWordsFounded = 0, indexFirstPosMatched =
0
    set indMatched = KMP(lengthsTxt, lengthsPatt)
    set finalResultIndexes as (emptyList)
    For (ind in indMatched)
        posMatched = ind/2
        indFirstWord = indexes[posMatched]
        indexFirstPosMatched = indFirstWord
            For (i = 0; i < sizePattWords; i += 2)
                Set   wSize=formatNumber(lengthsPatt.substr(i,
2))
                If          (pattern.substr(indexes[i/2],wSize)==
text.substr(indFirstWord, wSize)) Then
                    countPatternWordsFounded++
                    posMatched++
                Else
                    Break
                End
            indFirstWord = indexes[posMatched]
            End
            If (countPatternWordsFounded == wordsPatt) Then
                finalResultIndexes.push(indexFirstPosMatched)
                countPatternWordsFounded = 0
            End
    End
    return finalResultIndexes
End
```

Since the algorithm makes use of the information from the structure of the text, parameters are added to the search, corresponding to the lengths and positions of the words in the texts. Below is an example of the input parameters for the hybrid algorithm based on Fig. 1: 1) text: “HELLO FRIENDS, HOW ARE YOU?”, 2) pattern: “HOW ARE”, 3) lengthsTxt: “0507030303”, 4) lengthsPatt: “0303”, 5) indexes: “0,6,15,19,23”. In this case, the alphanumeric characters constitute the information to obtain the lengths in the preprocessing phase, while the remaining characters are part of the separators.

## V. Performance Comparison

### A. Selection of Algorithms for Experiments

In text pattern searching, the KMP and BM algorithms are widely recognized for their efficiency and ability to process large datasets. Their design incorporates features that enable them to surpass the limitations of simpler methods, such as brute-force search.

The KMP algorithm optimizes the search process by minimizing unnecessary comparisons through the use of a shift table that stores information about previous matches. This approach maintains a time complexity of O(n+m), which is significantly more efficient than traditional brute-force search, which can reach O(n*m). This efficiency is especially valuable in situations where multiple searches on the same text are required [6].

Conversely, the BM algorithm is highly efficient due to its use of advanced heuristics, such as the bad-character rule and the good-suffix rule. These techniques allow the algorithm to skip large portions of text rather than examining each character sequentially, leading to outstanding performance, particularly when searching for long patterns within extensive texts. This algorithm can achieve a complexity of O(n/m) in its best-case, making it very attractive for applications where speed and efficiency are crucial [5].

Due to their ability to reduce processing time, optimize memory usage, and enhance search accuracy, both algorithms are widely used in applications requiring high-speed text searching, such as search engines and text analysis tools. Consequently, KMP and BM remain among the most effective algorithms for pattern searching in computer science.

In this study, KMP and BM are compared with the proposed hybrid algorithm that combines structural preprocessing based on word lengths with the KMP algorithm. This proposal emerged after observing that an approach based solely on word lengths was not sufficient. Thus, a hybrid approach was developed to improve performance, and its evaluation is presented in the following sections.

### B. Complexity of Algorithms

The complexity analysis of the proposed algorithm shows that in the worst-case the complexity is O(n*m). This calculation is obtained by considering the following phases of the algorithm: During the preprocessing phase, a traversal is performed over the text and the pattern to compute the size of each word, which results in a cost of O(n + m), where 'n' is the length of the text and 'm' is the length of the pattern. Subsequently, the KMP algorithm is employed, which operates with a complexity of O(n+m). Nevertheless, in the final step, when traversing the vector that contains the indices of the substrings with the same length as the pattern and performing character-by-character comparisons between the substring and the pattern, the worst-case complexity increases to O(n*m).

By contrast, in the best-case scenario, when the pattern consists of a single word, the complexity in the final step is reduced to O(n*1), which keeps the overall complexity at O(n+m).

Table I presents a comparison of the best and worst case complexity between the algorithms used in the experiments.

TABLE I. COMPARISON OF ALGORITHMS COMPLEXITY

| Algorithm | Best Case Complexity | Worst Case Complexity |
|---|---|---|
| KMP (Knuth-Morris-Pratt) | O(n+m) [9] | O(n+m) [9] |
| BM (Boyer-Moore) | O(n/m) [5][11] | O(n*m) [14] |
| Hybrid (LP-KMP) | O(n+m) | O(n*m) |

## VI. EXPERIMENTAL RESULTS

The hybrid algorithm and the comparison software for the selected algorithms were executed on a personal computer with the specifications listed in Table II. The algorithm was developed using Microsoft Visual Studio, and the C++ compiler was used for compilation and execution.

TABLE II. SYSTEM INFORMATION

| Resource | Description |
|---|---|
| Processor | Intel(R) Core(TM) i5-9300H 2.4GHz (8CPUs) |
| Memory | 8192 MB RAM |
| Operating System | Windows 11 Home 64-bit |

To evaluate the performance of the algorithms, a set of experiments was designed and classified into two groups. The first group corresponds to artificially created scenarios [15], in which computer-generated texts were constructed using fixed-length words and controlled repetitive patterns. The second group corresponds to real-world scenarios [16], consisting of public domain classical texts.

In the artificial scenarios, text files were generated with a predefined number of repeated words, all of the same length. Within these texts, specific words designated as occurrences were inserted, serving as search patterns. In these experiments, the BM, KMP, and the proposed hybrid algorithm PL-KMP were evaluated.

The tests were conducted under controlled conditions, measuring the number of CPU cycles required by each algorithm to locate the occurrences. The results corresponding to this first group of experiments are presented in Tables III, IV, and V, and are graphically illustrated in Fig. 3 to Fig. 14.

TABLE III. TEXT SCENARIOS CREATED WITH 1-CHARACTER WORDS

| Number of Words | Occurrences | BM | KMP | LP-KMP |
|---|---|---|---|---|
| 5000 | 1 | 496404 | 1645344 | 6054392 |
| 5000 | 3 | 618372 | 1838636 | 7911064 |
| 5000 | 5 | 511716 | 1661372 | 7691332 |
| 10000 | 1 | 1623122 | 5440384 | 19853538 |
| 10000 | 3 | 1620814 | 5462448 | 20295200 |
| 10000 | 5 | 1641032 | 5427442 | 20015822 |
| 15000 | 1 | 2430706 | 8101176 | 29889788 |
| 15000 | 3 | 2428924 | 8222824 | 29758070 |
| 15000 | 5 | 2431012 | 8243022 | 29865682 |
| 20000 | 1 | 1894232 | 6497074 | 23494778 |
| 20000 | 3 | 1886316 | 6342556 | 23382132 |
| 20000 | 5 | 1896082 | 6346574 | 23916868 |

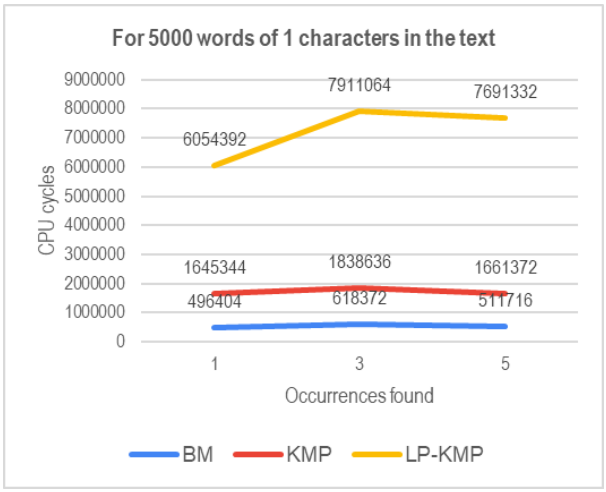


Fig. 3. Comparison of searches in texts of 5000 words of 1 character each word.

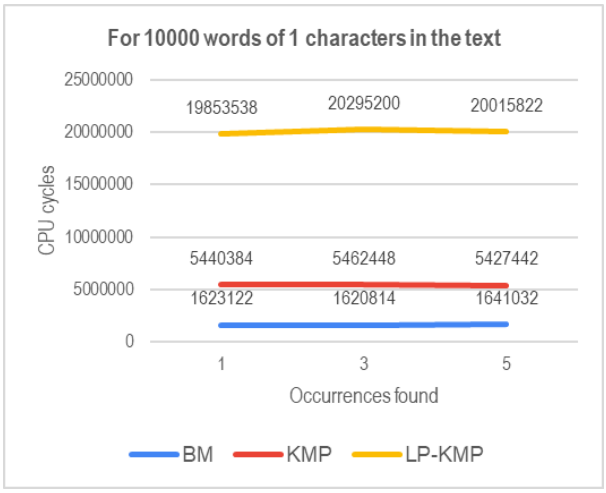


Fig. 4. Comparison of searches in texts of 10000 words of 1 character each word.

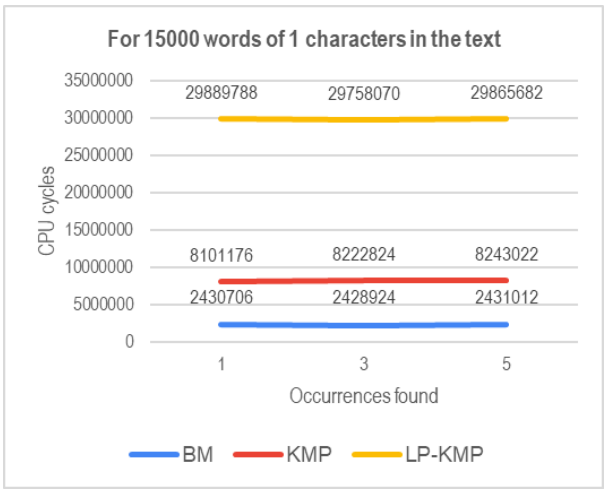


Fig. 5. Comparison of searches in texts of 15000 words of 1 character each word.

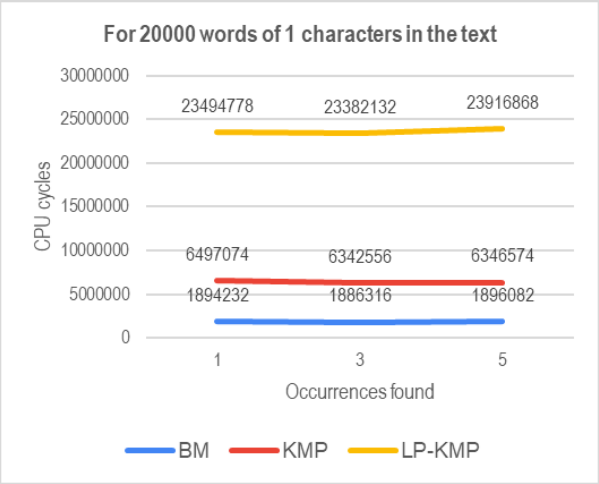


Fig. 6. Comparison of searches in texts of 20000 words of 1 character each word.

TABLE IV. TEXT SCENARIOS CREATED WITH 3-CHARACTER WORDS

| Number of Words | Occurrences | BM | KMP | LP-KMP |
|---|---|---|---|---|
| 5000 | 1 | 981200 | 1098608 | 6277770 |
| 5000 | 3 | 975608 | 1101816 | 6146920 |
| 5000 | 5 | 955380 | 1066634 | 6137210 |
| 10000 | 1 | 1956372 | 2184216 | 15324210 |
| 10000 | 3 | 2134800 | 2192866 | 12661116 |
| 10000 | 5 | 1955818 | 2294792 | 12539332 |
| 15000 | 1 | 2912518 | 3269166 | 31429612 |
| 15000 | 3 | 4846424 | 5439562 | 31367776 |
| 15000 | 5 | 4842008 | 5490228 | 31812352 |
| 20000 | 1 | 3859580 | 4224038 | 25805696 |
| 20000 | 3 | 3874884 | 4329296 | 24525460 |
| 20000 | 5 | 3773204 | 4225842 | 24736656 |

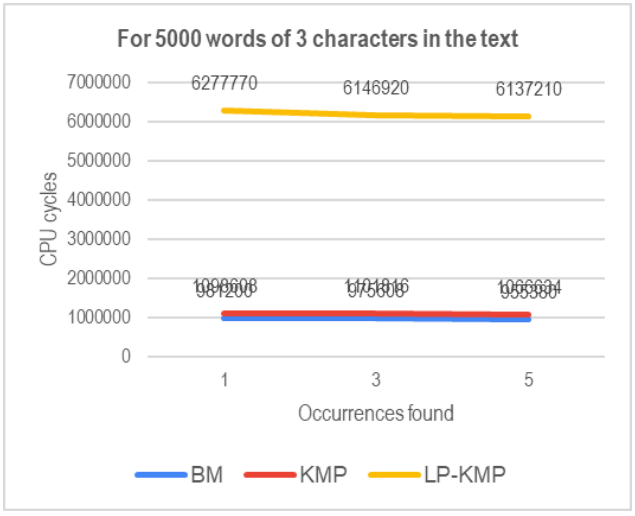


Fig. 7. Comparison of searches in texts of 5000 words of 3 characters each word.

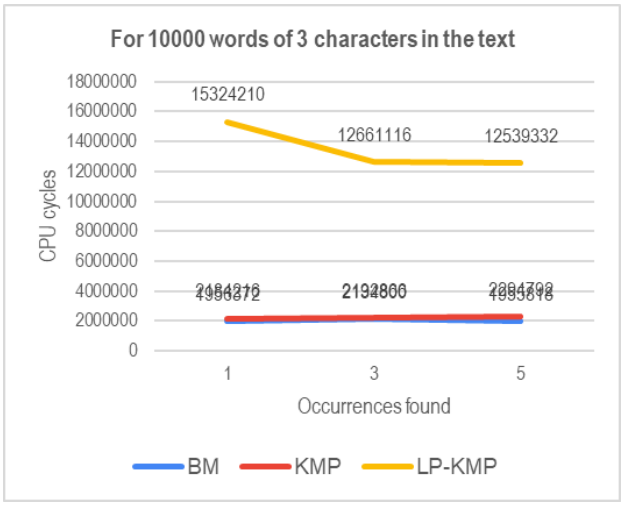


Fig. 8. Comparison of searches in texts of 10000 words of 3 characters each word.

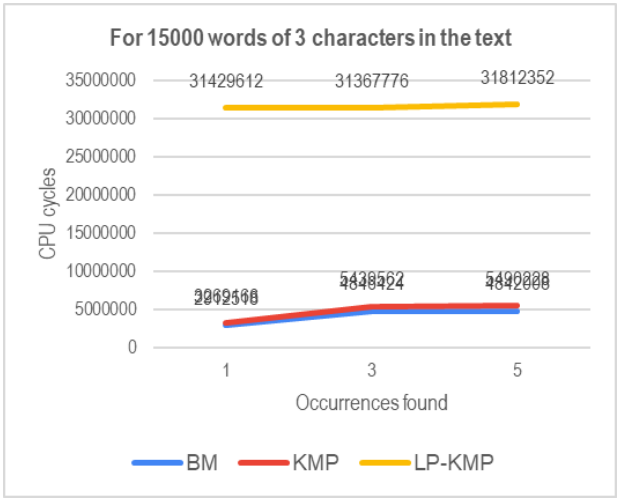


Fig. 9. Comparison of searches in texts of 15000 words of 3 characters each word.

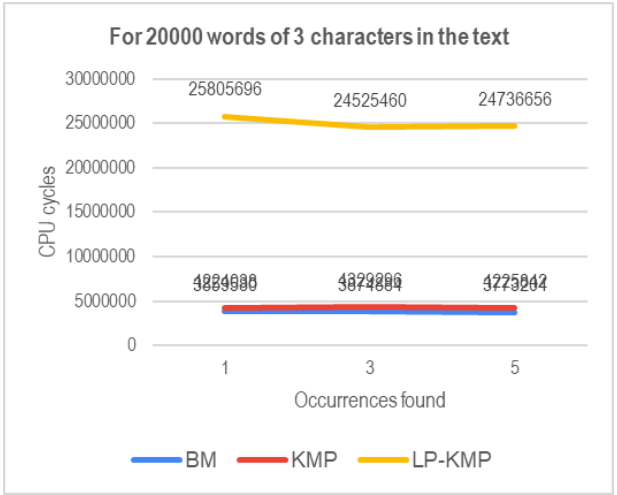


Fig. 10. Comparison of searches in texts of 20000 words of 3 characters each word.

TABLE V. TEXT SCENARIOS CREATED WITH 5-CHARACTER WORDS

| Number of Words | Occurrences | BM | KMP | LP-KMP |
|---|---|---|---|---|
| 5000 | 1 | 1464074 | 992586 | 8265800 |
| 5000 | 3 | 1481530 | 993654 | 10028736 |
| 5000 | 5 | 1448260 | 972152 | 6263314 |
| 10000 | 1 | 2842428 | 1927880 | 12150638 |
| 10000 | 3 | 2857908 | 1926674 | 12423264 |
| 10000 | 5 | 3181448 | 1945964 | 12134070 |
| 15000 | 1 | 4253702 | 2861360 | 18489042 |
| 15000 | 3 | 4269750 | 2865512 | 18541728 |
| 15000 | 5 | 4317254 | 2948970 | 18319860 |
| 20000 | 1 | 5652428 | 3815354 | 24354276 |
| 20000 | 3 | 5677966 | 3804260 | 24807472 |
| 20000 | 5 | 5674680 | 3814230 | 34425994 |

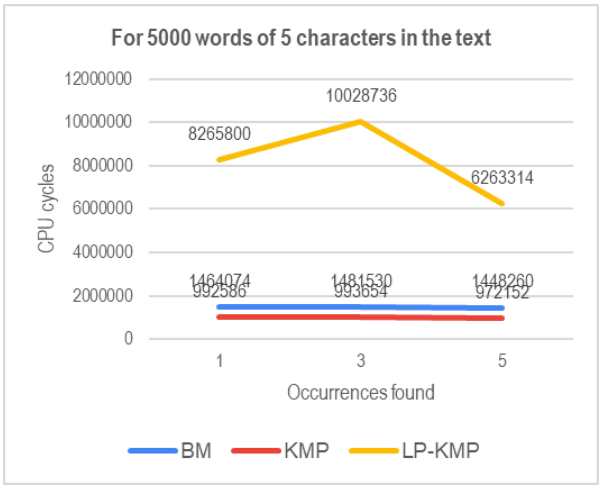


Fig. 11. Comparison of searches in texts of 5000 words of 5 characters each word.

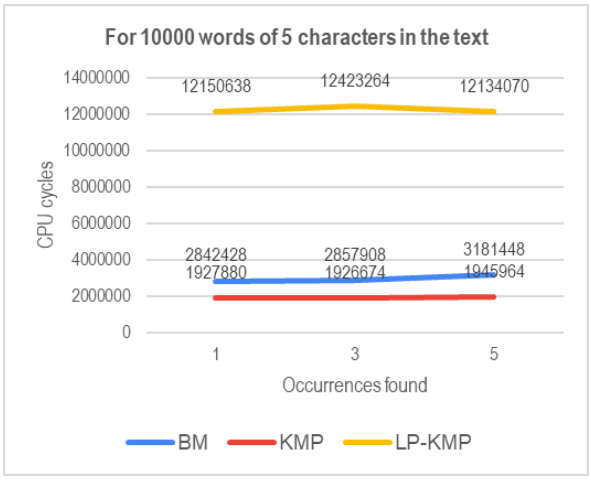


Fig. 12. Comparison of searches in texts of 10000 words of 5 characters each word.

A significant difference is evident in the approach of the proposed hybrid PL-KMP algorithm compared to the classical BM and KMP algorithms. In the evaluated scenarios, the hybrid algorithm does not outperform BM and KMP, primarily because its search mechanism performs between three to six times more operations for each detected match, thereby increasing the computational load in these cases.

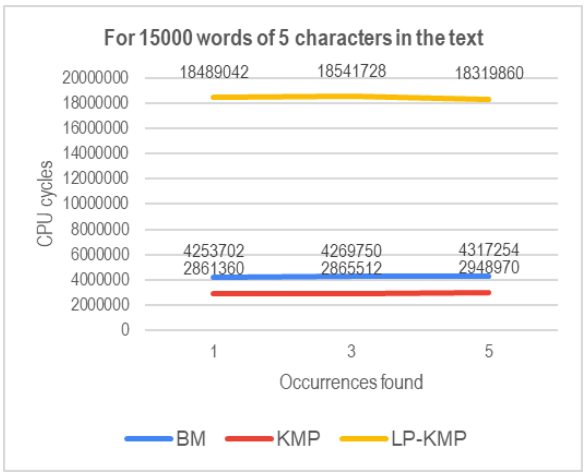


Fig. 13. Comparison of searches in texts of 15000 words of 5 characters each word.

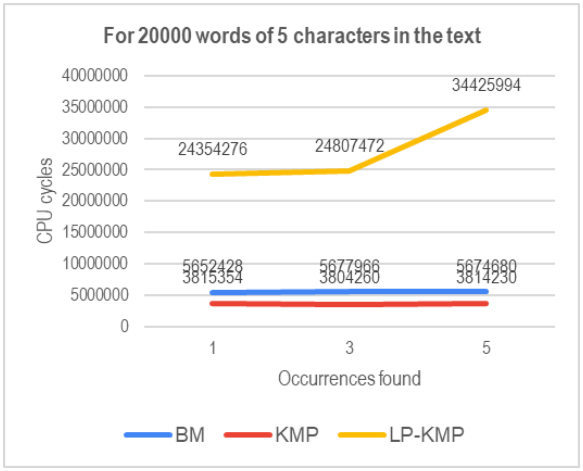


Fig. 14. Comparison of searches in texts of 20000 words of 5 characters each word.

In the second group of experiments, tests were conducted using five real-world texts corresponding to classic short stories. In these cases, the BM, KMP, and PL-KMP algorithms were again applied to search for patterns composed of one (1), three (3), and five (5) consecutive words. The results are presented in Tables VI and VII and are graphically illustrated in Fig. 15 to Fig. 17.

The results obtained in real-world scenarios highlight the true potential of the proposed hybrid algorithm. Compared to the KMP algorithm, which demonstrated the best performance in the most demanding synthetic scenarios, the hybrid algorithm managed to reduce the search time by more than half. This improvement is attributed to its preprocessing strategy based on length patterns, which enables the identification of structural matches prior to character-by-character comparison. By limiting comparisons only to cases where there is a preliminary match in word lengths, the total number of operations required is significantly reduced.

TABLE VI. EXPERIMENTS CREATED FOR REAL SCENARIOS

| Experiment | Test Text | | Number of Words | Number of characters | Words to search | Occurrences |
|---|---|---|---|---|---|---|
| 1 | 1 | Cinderella.txt | 249 | 1465 | "Cinderella" | 10 |
| 2 | 2 | Little Red Riding Hood.txt | 262 | 1457 | "little" | 3 |
| 3 | 3 | The Adventures of Pinocchio.txt | 371 | 1997 | "Pinocchio" | 10 |
| 4 | 4 | The Three Little Pigs.txt | 408 | 2058 | "built" | 3 |
| 5 | 5 | The Ugly Duckling.txt | 284 | 1608 | "ugly" | 5 |
| 6 | 1 | Cinderella.txt | 249 | 1465 | "for the ball" | 1 |
| 7 | 2 | Little Red Riding Hood.txt | 262 | 1457 | "talk to strangers" | 1 |
| 8 | 3 | The Adventures of Pinocchio.txt | 371 | 1997 | "magical place where" | 1 |
| 9 | 4 | The Three Little Pigs.txt | 408 | 2058 | "a house of" | 1 |
| 10 | 5 | The Ugly Duckling.txt | 284 | 1608 | "he found shelter" | 1 |
| 11 | 1 | Cinderella.txt | 249 | 1465 | "she turned a pumpkin into" | 1 |
| 12 | 2 | Little Red Riding Hood.txt | 262 | 1457 | "she walked through the forest" | 1 |
| 13 | 3 | The Adventures of Pinocchio.txt | 371 | 1997 | "who had been looking for" | 1 |
| 14 | 4 | The Three Little Pigs.txt | 408 | 2058 | "and rolled down the hill" | 1 |
| 15 | 5 | The Ugly Duckling.txt | 284 | 1608 | "and he saw a group" | 1 |

TABLE VII. COMPARISON OF ALGORITHMS IN REAL SCENARIOS

| Experiment | Test Text | | CPU Cycles | | |
|---|---|---|---|---|---|
| | | | BM | KMP | LP-KMP |
| 1 | 1 | Cinderella.txt | 215396 | 173092 | 127972 |
| 2 | 2 | Little Red Riding Hood.txt | 140676 | 91996 | 63636 |
| 3 | 3 | The Adventures of Pinocchio.txt | 158826 | 122350 | 89916 |
| 4 | 4 | The Three Little Pigs.txt | 227556 | 125174 | 108230 |
| 5 | 5 | The Ugly Duckling.txt | 185114 | 116140 | 110520 |
| 6 | 1 | Cinderella.txt | 280302 | 165592 | 74070 |
| 7 | 2 | Little Red Riding Hood.txt | 184168 | 177350 | 75862 |
| 8 | 3 | The Adventures of Pinocchio.txt | 203524 | 201518 | 92962 |
| 9 | 4 | The Three Little Pigs.txt | 304024 | 204744 | 85164 |
| 10 | 5 | The Ugly Duckling.txt | 199110 | 172962 | 61580 |
| 11 | 1 | Cinderella.txt | 236340 | 201708 | 75332 |
| 12 | 2 | Little Red Riding Hood.txt | 203252 | 171854 | 136352 |
| 13 | 3 | The Adventures of Pinocchio.txt | 181358 | 179920 | 90966 |
| 14 | 4 | The Three Little Pigs.txt | 201598 | 210324 | 100404 |
| 15 | 5 | The Ugly Duckling.txt | 183504 | 173764 | 67588 |

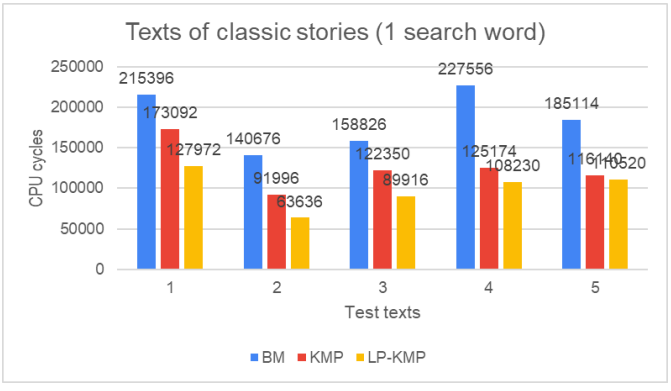


Fig. 15. Search for one (1) word in classic story texts.

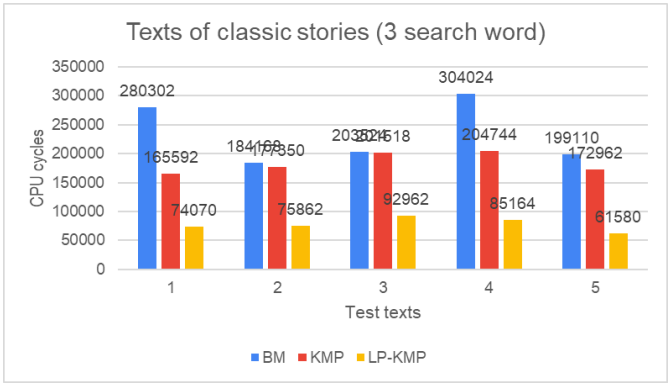


Fig. 16. Search for three (3) words in classic story texts.

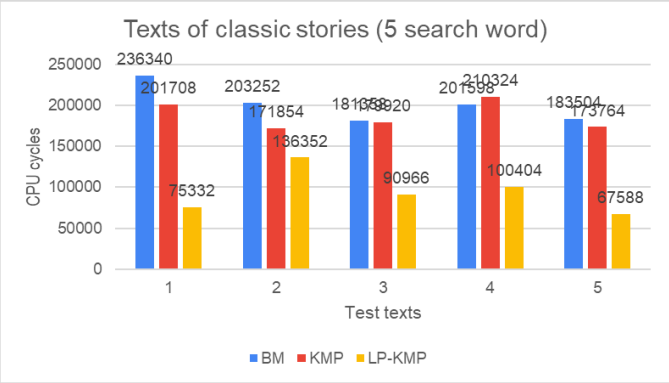


Fig. 17. Search for five (5) words in classic story texts.

## VII. Discussion

The experimental results reveal a differentiated behavior of the hybrid PL-KMP algorithm compared to the classical BM and KMP algorithms, depending on the type of text processed.

In synthetic texts—designed to represent highly repetitive scenarios with uniform-length patterns—the traditional algorithms demonstrated better performance. This is because they are optimized for direct character comparisons, allowing them to maintain a lower computational load in predictable contexts. In such cases, PL-KMP exhibited a higher number of operations, due to its strategy of validating matches only after identifying length-based pattern matches.

In contrast, in real-world texts—such as classic tales with natural linguistic structures and variable word lengths—the hybrid algorithm showed a substantial improvement in search time. This advantage is attributed to its preprocessing mechanism, which efficiently filters potential candidates before initiating character-by-character comparison. This strategy reduces unnecessary operations and improves performance in less structured contexts.

A notable feature of the algorithm is its flexibility in detecting text patterns even when they are separated by various delimiters (spaces, hyphens, or punctuation marks), which is not considered by classical methods based solely on exact matches.

Nonetheless, the proposed algorithm presents certain limitations. One of them is its inability to detect substrings embedded within longer words, since the algorithm relies on identifying length patterns before executing textual comparisons. This limitation represents an opportunity for improvement in future versions of the algorithm, which could incorporate more flexible internal validation mechanisms.

Another significant limitation is the absence of a standardized corpus for evaluating pattern matching algorithms in text. Unlike other areas of natural language processing, there are no widely accepted benchmark datasets for this purpose. Furthermore, many related studies do not publish their datasets, making it difficult to perform objective comparisons between different approaches.

To contribute to reproducibility and foster further research in this area, the datasets used in this study—both the artificial scenarios and the real-world texts—have been made publicly available [15], [16]. This initiative aims to establish a fairer and more standardized basis for comparing future text search algorithms.

## VIII. Conclusion

In this research, a hybrid text search algorithm has been developed and evaluated, which combines a structural preprocessing based on length patterns with the KMP algorithm. The experimental results demonstrate that, in scenarios with real texts and diverse linguistic structures, the hybrid algorithm outperforms traditional methods in terms of efficiency, thanks to its ability to reduce the number of comparisons through prior filtering.

In contrast, in highly structured synthetic scenarios, traditional algorithms like KMP and BM showed superior performance, as they are optimized for direct comparisons in uniform patterns.

The main advantages of the proposed algorithm include its high search speed in real texts and its flexibility to identify textual patterns even when they are separated by non-alphanumeric characters —such as hyphens, spaces, or punctuation marks. This feature allows for the equivalent identification of patterns such as “aaa-bbb-ccc,” “aaa bbb ccc,” or “aaa.bbb.ccc,” as long as the delimiters have been defined as excluded by the inclusion function.

However, a significant limitation of the algorithm is its inability to identify substrings contained within longer words, as the matching process is initially based on the sequence of lengths. This aspect represents an opportunity for improvement in future versions that incorporate more flexible search techniques after the initial filtering.

## IX. Future Work

As part of future work, the development of an improved version of the hybrid algorithm is proposed, which would enable the detection of patterns embedded within compact strings. This would overcome the current limitation of relying exclusively on exact matches in length sequences. A possible solution is the incorporation of partial search techniques applied to candidate fragments once preliminary structural similarities have been identified.

Additionally, the adaptation of the algorithm to multilingual environments is considered, which would open up possibilities for its application in more diverse contexts such as information retrieval systems, search engines, or large-scale text analysis.

Finally, it is proposed to investigate the integration of the algorithm with machine learning techniques, with the aim of dynamically optimizing preprocessing criteria based on the linguistic characteristics of the text. This integration would enable greater adaptability and efficiency in real-world applications.

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# Pothole Detection: A Study of Ensemble Learning and Decision Framework

Ken D. Gorro[1]*, Elmo B. Ranolo[2], Anthony S. Ilano[3], Deofel P. Balijon[4]
Center for Cloud Computing, Big Data and Artificial Intelligence, Philippines[1, 2, 3]
College of Computing, Artificial Intelligence and Sciences of Cebu Normal University, Philippines[4]

***Abstract*—This study investigates the potential use of ensemble learning (YOLOv9 and Mask R-CNN) and Multi-Criteria Decision Making for pothole detection system. A series of experiments were conducted, including variations in confidence thresholds, IoU thresholds, dynamic weight configurations, camera angles and MCDM criteria, to assess their effects on detection performance. The YOLOv9 model achieved a mean Average Precision (mAP) of 0.908 at 0.5 IoU and an F1 score of 0.58 at a confidence threshold of 0.282, indicating a strong balance between precision and recall. However, adjusting IoU thresholds showed that lower thresholds improved recall but resulted in false positives, while higher thresholds improved precision but reduced recall. Dynamic weight configurations were explored, with balanced weights (wY = 0.5, wM = 0.5) yielding the best overall performance, while uneven weights allowed trade-offs between precision and recall based on specific application needs. The MCDM framework refined detection outputs by evaluating pothole features such as size, position, depth, and shape. The proposed algorithm has the potential to be widely used in practical applications. Overfitting is the main drawback of the proposed algorithm, but this is dependent on the use case where the pothole detection will be used.**

**Keywords—*YOLO; Mask R-CNN; ensemble learning; MCDM***

## I. Introduction

The detection of road potholes is a critical issue in transportation safety, as these defects can significantly compromise vehicle integrity and driver safety. Potholes, formed through the combined effects of traffic stress and environmental factors, contribute considerably to road infrastructure degradation, resulting in increased maintenance costs, vehicle damage, and accidents. Studies indicate that potholes accounted for approximately 0.8% of road accidents in 2021, contributing to 1.4% of fatalities and 0.6% of injuries annually [1]. Additionally, the deterioration of road surfaces due to heavy traffic and adverse weather conditions can lead to potholes as deep as 10 inches [2]. This affects vehicle performance and increases operational costs for drivers, with potholes estimated to add approximately $3 billion annually in costs in Canada alone [3].

Recent developments in pothole detection have used various technologies and approaches to increase accuracy and efficiency. Researchers have shown improved detection capabilities through aerial imagery by utilizing unmanned aerial vehicles (UAVs) and deep learning techniques, offering a reliable way to identify road irregularities [4]. Similarly, YOLO models have been investigated for real-time pothole identification, demonstrating their efficacy in computer vision-based systems [5]. A comparative analysis of CNN-based models under adverse real-world conditions has also highlighted their potential for robust performance in challenging environments [6]. Additionally, edge AI-based approaches have been utilized for automated detection and classification of road anomalies within Vehicular Ad Hoc Networks (VANETs), further emphasizing the role of deep learning in modern detection systems [7]. Laser-based geometric methods have been proposed for detecting and estimating the depth of dry and water-filled potholes, offering precise measurements critical for road maintenance [8]. Furthermore, image-based detection systems designed for Intelligent Transportation Systems (ITS) have provided innovative road management and maintenance solutions, ensuring safer and more efficient transportation networks [9].

Multi-Criteria Decision-Making (MCDM) is a decision-support methodology used to evaluate and rank multiple alternatives based on several conflicting criteria. MCDM is widely applied in fields such as engineering, economics, and artificial intelligence to optimize complex decision-making processes. You Only Look Once (YOLO) is a deep learning-based object detection algorithm known for its speed and accuracy. YOLO treats object detection as a single-pass regression problem, meaning it predicts bounding boxes and class probabilities in real-time.

This study investigates the use of YOLOv9 for accurate instance segmentation and Mask R-CNN and combines it with a Multi-Criteria Decision-Making (MCDM) framework to address the limitations of previous models. While earlier YOLO-based approaches, such as YOLOv8, demonstrated effectiveness in marking and detecting potholes, they lacked the capability to identify potholes that are not deep but still contribute to road imbalance [10]. This limitation is significant, as shallow yet widespread potholes can also pose risks to vehicle stability and safety. The YOLOv8 model achieved training and validation losses of 0.06 and 0.04, respectively, but its reliance on bounding boxes restricted its ability to capture geometric details and assess the impact of individual potholes accurately. Similarly, the study by Gorro et al. employed YOLOv8 for pothole detection using bounding boxes [11]. While the results were promising, the approach struggled to detect potholes that are not deep but have larger dimensions, which can still cause significant road imbalance. This limitation led to increased false positives [11].

Existing pothole detection methods face key limitations, including poor segmentation of shallow yet wide potholes,

*Corresponding Author.

limited integration of spatial and contextual features, and lack of decision-level fusion for prioritization. Most rely solely on bounding boxes or basic classification without refined post-processing or evaluation strategies.

To bridge these gaps, this study introduces an ensemble framework combining YOLOv9 and Mask R-CNN for accurate segmentation, alongside an MCDM-based approach to rank potholes by severity. The proposed method is validated through extensive experiments demonstrating its robustness and improved detection performance.

This study performs different experiments on the proposed algorithm to determine the drawbacks of the proposed algorithm. Ensemble learning ensures that both models collaborate to detect potholes robustly, using YOLOv9 for rapid instance segmentation and Mask R-CNN for precise boundary refinement. This study focuses on the research question:

Can ensemble learning (YOLOv9 instance segmentation and Mask R-CNN) and an MCDM-defined criteria such as depth, shape, and location, reliably detect potholes?

This study presents the basic results of each step in YOLOv9 training, as well as the results of various experiments conducted, starting with ensemble learning and the integration of MCDM. Additionally, this study presents experiments aimed at determining the limitations of the proposed algorithm.

## II. Literature Review

### A. Pothole Detection Approaches

Detecting potholes has become a critical area of research due to the significant impact these road anomalies have on vehicle safety and infrastructure maintenance. Various methods have been developed to identify and assess potholes, which can be broadly categorized into computer vision-based models, sensor-based techniques, and deep learning approaches.

Computer vision techniques have been widely employed for pothole detection, lever- aging image processing algorithms to analyze road conditions. Early works, such as those by Koch and Brilakis, utilized texture analysis and machine learning classifiers to distinguish between pothole and non-pothole pavement textures, achieving improved accuracy through parameter optimization [12]. Ryu et al., further advanced this field by proposing an image-based pothole detection system that integrates various features for enhanced detection performance, although it requires more processing time compared to simpler methods [13]. More recent approaches, such as those reviewed by Ma et al., highlight the evolution of computer vision techniques from classical 2D image processing to 3D point cloud modeling, emphasizing the effectiveness of convolutional neural networks (CNNs) in achieving high detection accuracy [14]. However, these vision-based methods are often sensitive to environmental conditions, such as lighting and surface water, which can hinder detection accuracy [15].

Sensor-based methods typically involve the use of accelerometers and other vibration sensors to detect potholes based on the physical responses of vehicles traversing affected areas. For instance, vibration-based methods have been shown effectively to identify road anomalies by analyzing the signals produced when vehicles pass over potholes [16]. Although these methods can provide direct measurements of road conditions, they may miss detections if the vehicle, does not directly traverse the pothole, leading to potential gaps in data [17]. Additionally, some studies have explored the integration of sensor data with image processing techniques to enhance detection capabilities, combining the strengths of both approaches [18]. Deep learning has emerged as a powerful tool for pothole detection, particularly through the application of CNNs. Recent studies, such as those by Dewangan and Sahu, have demonstrated the effectiveness of CNNs in achieving high precision and recall rates for pothole detection, outperforming traditional methods [19]. Furthermore, the YOLO (You Only Look Once) framework has gained traction for its ability to perform real-time detection, allowing for rapid identification and classification of potholes in various conditions [20]. The adaptability of deep learning models to different datasets and their capacity for continuous learning make them particularly promising for future pothole detection systems [21]. However, challenges remain in terms of data quality and the need for extensive training datasets to ensure robust performance across diverse environments [22].

### B. Multi-Criteria Decision Making

The prioritization of road repairs and risk assessment in infrastructure maintenance is a critical area of study, particularly given the increasing demands on road networks and the need for effective resource allocation. Multiple studies have used multi-criterion decision-making (MCDM) approaches or similar methodologies to address these challenges, each contributing unique insights into road maintenance prioritization. One notable study by Orugbo et al. utilized a hybrid model combining Reliability-Centered Maintenance (RCM) and the Analytic Hierarchy Process (AHP) to prioritize maintenance for trunk road networks. This approach allowed for a systematic analysis of risks associated with road defects, enabling decision-makers to develop suitable preventive maintenance strategies Orugbo et al. [23]. The integration of AHP facilitated the decomposition of complex maintenance decisions into manageable components, allowing for a more nuanced understanding of conflicting objectives and multi-criteria evaluations. Similarly, Agabu's research focused on sustainable prioritization of public asphalt-paved road maintenance, emphasizing the need for a robust framework that incorporates various factors such as road condition, traffic levels, safety, and environmental considerations [24]. This study highlights the complexity of decision-making in road maintenance, where multiple criteria must be balanced to achieve equitable outcomes under budget constraints.

Bikam's work on logistical support for road maintenance in Vhembe district municipalities underscores the importance of planned maintenance in reducing road accidents and disaster risks. By utilizing Geographic Information Systems (GIS) for monitoring and planning, the study advocates for a proactive approach to road maintenance that can lead to significant long-term savings and enhanced safety [25]. This aligns with the broader trend of employing data-driven methodologies to inform maintenance decisions. In another study, Adnyana and Sudarsana applied the STEPLE method for risk analysis in road

maintenance projects in Bali. This method assesses the potential negative impacts on stakeholders and the environment during construction, emphasizing the need for comprehensive risk management strategies in infrastructure projects [26]. Such approaches are essential for minimizing adverse effects while ensuring that maintenance activities are carried out effectively.

Augeri et al. proposed an interactive multiobjective optimization approach for urban pavement maintenance, combining the Interactive Multiobjective Optimization (IMO) with the Dominance-based Rough Set Approach (DRSA). This innovative framework allows for the consideration of multiple objectives and constraints, facilitating a more effective decision-making process in road maintenance management [27]. The ability to incorporate stakeholder preferences into the optimization process enhances the relevance and applicability of the maintenance strategies developed. Moreover, a study introduce a Score Card Utility Matrix for prioritizing asphalt-paved road maintenance projects, illustrating the complexity of decision-making in this domain [28]. This matrix allows for a structured evaluation of various criteria, aiding local and international road authorities in making informed prioritization decisions [28].

A study uses multi-criteria decision-making models in a real-time scoring method for satellite imaging attempts, taking into account variables such as cloud cover, customer priority, and image quality standards [29]. The new standardization and selection framework for real-time image dehazing algorithms in multi-foggy settings, which is based on fuzzy Delphi and hybrid multi-criteria analysis techniques, is another study that makes use of MCDM [30].

### C. Limitations of Existing Studies

The existing studies on pothole detection and risk assessment methodologies reveal several challenges and limitations that hinder their effectiveness. These limitations can be categorized into issues related to depth estimation, integration with risk assessment models, and the overall robustness of detection methods.

Many current pothole detection methods, particularly those based on image processing and computer vision, struggle with accurately estimating the depth of potholes. For instance, while some studies utilize 2D imaging techniques, they often fail to provide comprehensive depth information, which is critical for assessing the severity of road anomalies and planning maintenance strategies [31]. Wang et al. highlighted that traditional methods relying on single thresholds for detection often yield high false positives, which can obscure the true condition of the road surface [32]. Without accurate depth estimation, maintenance prioritization may be misguided, leading to either over-investment in minor issues or neglect of more severe problems.

Another significant limitation is the insufficient integration of pothole detection systems with comprehensive risk assessment models. Many existing approaches focus solely on detection without considering the broader implications of potholes on road safety and infrastructure resilience. For example, while Dewangan and Sahu's model achieved promising detection rates, it did not incorporate risk factors associated with pothole impacts on vehicle safety or infrastructure longevity [33]. Similarly, Koch and Brilakis emphasized the need for machine-learning techniques to classify pavement textures but did not address how these classifications could inform risk assessments or maintenance strategies [33]. The lack of a holistic approach that combines detection with risk evaluation can lead to suboptimal decision-making in road maintenance.

Real-time detection capabilities are essential for effective pothole management, yet many methods face challenges in processing speed and accuracy. Ryu et al. noted that their proposed method required significant processing time, which could hinder its application in real-time scenarios [34]. This limitation is compounded by the need for extensive data pre-processing and feature extraction, which can delay the detection process and reduce the system's responsiveness to emerging road hazards. Additionally, the reliance on high-quality images and favorable environmental conditions can further limit the effectiveness of these systems, as adverse weather or poor lighting can significantly impact detection accuracy [35], [36].

Many advanced detection methods, such as those utilizing stereo vision or deep learning algorithms, require sophisticated hardware and software setups that may not be feasible for all municipalities or road maintenance authorities. For instance, while stereo vision techniques can provide 3D measurements, they necessitate complex calibration processes and high computational power, which may not be readily available in all contexts [37]. This reliance on advanced technologies can create disparities in the implementation of pothole detection systems, particularly in resource-limited settings.

## III. Materials and Methods

### A. System Overview

Fig. 1 shows the general overview of our proposed pothole detection system. It shows the overview of how ensemble learning is performed and how to apply MCDM in the pothole detection problem. The details of each process is explained in the later section of this study.

### B. YOLOv9 Model for Pothole Detection

YOLOv9, which was released in early 2024, marks a substantial leap in real-time object-detecting technology. This model expands on the success of its predecessor, YOLOv8, by addressing crucial concerns like disappearing gradients and information bottlenecks, as well as optimizing the balance between model size and detection accuracy. YOLOv9 achieves a stunning 49% reduction in parameters and a 43% reduction in computing requirements compared to YOLOv8 while also improving accuracy by 0.6% [38]. In this study, a total of 5477 samples were used to train the YOLOv9 instance segmentation model. The 5477 samples include augmented samples. The augmentation techniques and the ratio of the training and testing set that were used in this study are the following:

Augmentations

Outputs per training example: 3 Rotation Between -15° and +15° Shear: ±10° Vertical

Dataset Splitting

train_set = 5477 images (82%)

valid_set = 608 images (9%)

test_set = 608 images (9%)

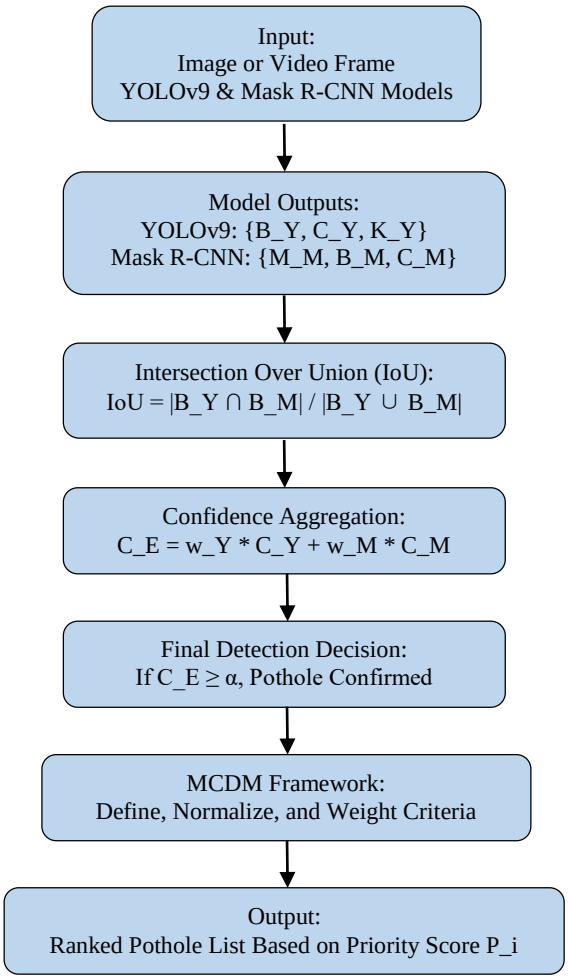


Fig. 1. System overview.

### C. Mask R-CNN

Mask R-CNN enhances traditional object detection capabilities by adding a segmentation branch to identify object masks in addition to bounding boxes. This capability is particularly beneficial for accurately delineating potholes from the surrounding road surfaces, providing more detailed information essential for effective decision-making in infrastructure management [39]. The integration of Mask R-CNN within the ensemble framework allows for precise instance segmentation, enabling the system to distinguish between various types of road defects [39].

### D. Final Algorithm

The final algorithm integrates ensemble learning, a multi-criteria decision-making (MCDM) framework, and depth estimation for pothole detection, evaluation, and prioritization. Below are the detailed steps of the algorithm, with explanations for each parameter and its purpose in the context of the algorithm.

1. Input:
   - Source: Image or video frame that serves as the input for the detection system.
   - Models: YOLOv9 and Mask R-CNN are utilized for ensemble learning to improve detection accuracy and robustness.
   - Camera Parameters:
     - H: Camera height from the ground, which is essential for accurately estimating the depth of potholes.
     - θ: Camera angle relative to the ground, which contributes if depth calculation by determining how the camera perceives object dimensions in the scene.

2. Model Outputs:
   - YOLOv9 outputs:

$$\{B_Y, C_Y, K_Y\}$$

   where,
     - $B_Y$: Bounding boxes for detected objects, which define the rectangular area around each detected pothole
     - $C_Y$: Confidence scores indicating the detection reliability for each bounding box.
     - $K_Y$: Classes of detected objects (e.g., pothole or non-pothole) for classification.
   - Mask R-CNN outputs:

$$\{M_M, B_M, C_M\}$$

   where,
     - $M_M$: Instance masks that highlight the exact shape and area of detected objects.
     - $B_M$: Bounding boxes for detected objects, similar to YOLOv9.
     - $C_M$: Confidence scores for the Mask R-CNN detections.

3. Intersection over Union (IoU): To compare overlapping detections:

$$\text{IoU} = \frac{|B_Y \cap B_M|}{|B_Y \cup B_M|}$$

   where,
   - $B_Y$ and $B_M$: Bounding boxes from YOLOv9 and Mask R-CNN, respectively.
   - $|B_Y \cap B_M|$: The area of overlap between the two bounding boxes.
   - $|B_Y \cup B_M|$ : The total area covered by both bounding boxes combined.

- Purpose: IoU is used to evaluate the consistency of detections between the two models, enabling better decision-making in ensemble learning.

4. Dynamic Weight Calculation: For each overlapping detection:

- Compute dynamic weights based on confidence scores and depth:

$$w_Y = \frac{C_Y \cdot D_Y}{C_Y \cdot D_Y + C_M \cdot D_M},\ w_Y = \frac{C_M \cdot D_M}{C_M \cdot D_Y + C_M \cdot D_M}$$

where,

- $w_Y$, $w_M$: Dynamic weights assigned to YOLOv9 and Mask R-CNN detections, respectively.
- $D_Y$, $D_M$: Depth values associated with YOLOv9 and Mask R-CNN detections.
- Purpose: Dynamic weights emphasize the contribution of each model's output based on its confidence and depth relevance, improving the overall accuracy.

5. Confidence Aggregation: Combine confidence scores dynamically as:

$$C_E = w_Y \cdot C_Y + w_Y \cdot C_M$$

where, $C_E$: Final aggregated confidence score for each detection.

- Purpose: Aggregating confidence scores ensures that detections from both models contribute proportionally to the final decision.

6. Final Detection Decision: A pothole is confirmed if:

$C_E \geq \alpha$

where, α: Predefined confidence threshold.

- Purpose: This threshold ensures that only highly reliable detections are considered as potholes.

7. Depth Estimation:

(a) Extract the largest contour of the pothole mask.

(b) Compute shadow intensity and relative shadow area R.

(c) Calculate depth:

$$\text{Depth} = H \cdot \tan(\theta) \cdot R$$

where,

- H: Camera height.
- θ: Camera angle.
- R: Relative shadow area of the pothole.
- Purpose: Depth estimation provides critical information for assessing the severity of the pothole.

(d) Overlay the estimated depth on the detected pothole.

8. Multi-Criteria Decision Making (MCDM):

(a) Define criteria:

- S: Size of the pothole (area in pixels).
- C: Aggregated confidence score.
- L: Location proximity to the road center.
- D: Depth of the pothole (from depth estimation).

(b) Compute criteria weights $w_j$: Weights are determined based on one of the 307 following methods:

- Predefined Weights: Assigned by experts based on safety concerns. Eg:

$$w_S = 0.2,\ w_C = 0.3,\ w_L = 0.1,\ w_D = 0.4$$

Higher weights are given to depth and confidence to prioritize hazardous potholes.

- Adaptive Weights: Computed dynamically using real-time detection confidence and depth:

$$w_j = \frac{F_j}{\sum_{k=1}^{n} F_k},$$

where, $F_j$ represent depth, confidence, or area. This method prioritizes potholes with higher detection reliability and severity.

- Entropy-Based Weights: Derived from data variability:

$$H_j = k \sum_{i=1}^{m} p_{ij}\, In(p_{ij})$$

where, $p_{ij}$ is the normalized value for each criterion. The final weights are:

$$w_j = 1 - H_j$$

This ensures that criteria with high variance receive greater influence in decision-making.

For this work, the weights are defined as:

$$w_S + w_C + w_L + w_D = 1$$

where, $w_S$, $w_C$, $w_L$, $w_D$ are the normalized contributions of each criterion.

(c) Normalize criteria:

$$X_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

where, $X_{ij}$ is the normalize value of criterion *j* of pothole *i*.

(d) Compute weighted score:

$$P_i = \sum_{j=1}^{n} w_j \,.\, X_{ij}$$

where:

- $P_i$: Priority score for pothole *i*.
- $w_j$: Weights assigned to each criterion, dynamically computed or predefined.

(e) Purpose: MCDM ranks potholes based on their severity and repair priority, ensuring efficient road maintenance decisions.

9. Evaluation Metrics:

(a) Circularity: For shape verification:

$$\text{Circularity} = \frac{4\pi \cdot Area}{\text{Perimeter}^2}$$

(b) Size Measurement:

$$A = \sum_{x,yCM_E} 1$$

(c) Centroid and Location:

$$x_C = \frac{\sum_{x,yCM_E} x}{A}, Y_C = \frac{\sum_{x,yCM_E} y}{A}$$

where,

- $x_C, y_C$: The centroid coordinates of the detected pothole.
- Centroid: The centroid represents the geometric center of the pothole mask. It is calculated as the weighted average of the pixel positions within the pothole's detected area.
- Purpose: The centroid helps determine the pothole's location on the road, which is essential for prioritizing repairs based on proximity to high-traffic areas.

10. Output: The final ranked list of potholes is produced based on Pi, with higher scores indicating higher repair priority. Depths are displayed alongside confidence and shape metrics.

## IV. Result and Discussion

Fig. 2 illustrates the training and validation results for the YOLOv9e instance segmentation model, showing strong learning and stable performance. All box, segmentation, classification, and distribution focal loss smoothed curves are consistently decreasing, and that shows that the model performance, on object localization, segmentation, and classification, is improving. We observe a similar trend for validation losses, and it seems our segmentation loss began to increase a bit at around 40 epochs, suggesting some overfitting could occur, but may have been curbed through the use of regularization or early stopping. Overall, the results are promising for the localization and segmentation model, with large Intersection over Union scores on validation datasets indicating that extrapolation from our training set is unlikely to be a major issue for real-world applications, though further tuning may help address overfitting trends in our validation loss, which points to improvement in segmentation performance.

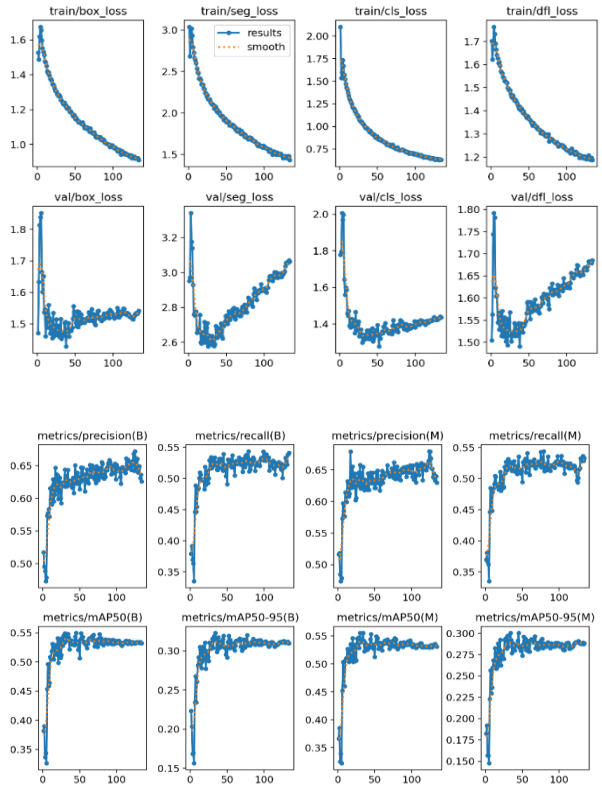


Fig. 2. Training and validation losses (box, segmentation, classification, and DFL) along with precision, recall, mAP@50, and mAP@50-95 metrics for bounding boxes (B) and masks (M). Solid lines indicate raw results, while dotted lines represent smoothed trends, showing the model's convergence over 120 epochs.

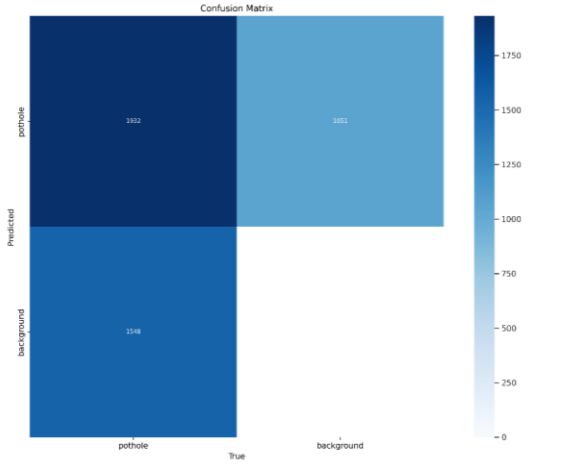


Fig. 3. Confusion matrix result.

Fig. 3 shows the confusion matrix that provides a numerical evaluation of the YOLOv9e model's pothole detecting performance. The matrix is created by classifying the following:

- True Positives (TP): 1,932 potholes that the model identified as such.

- False Negatives (FN): 1,548 actual potholes were categorized as background by the model.
- False Positives (FP): The model predicted 1,051 background instances as potholes.
- True Negatives (TN): The number of background instances correctly classified as background = 0.

Using these values, the model's performance metrics are calculated as follows:

$$Precision = \frac{TP}{TP + FP} = \frac{1{,}932}{1{,}932 + 1{,}051} \approx 64.7\%$$

$$\text{Recall} = \frac{TP}{TP + FP} = \frac{1{,}932}{1{,}932 + 1{,}548} \approx 55.5\%$$

These results suggest that the overall detection performance of the model is limited by a simple distinguishing background from potholes. With a proportion of likely inability to detect certain pothole features (44.5%), it supports the idea that subtle or less explicit pothole characteristics may be overlooked, instead identified as non-pothole features and retained, such as depth of disturbance, peeling of road surface, and absence of color change in a poorly disturbed condition.

The better the optimization, the more this can be applied in real life. Potential approaches may include better feature extraction, more diverse and representative training data, or tuning of decision thresholds to trade off precision and recall. By solving these aspects, you mitigate the risk of getting false negatives/positives and ensure the robustness and reliability of the model for real-world use cases.

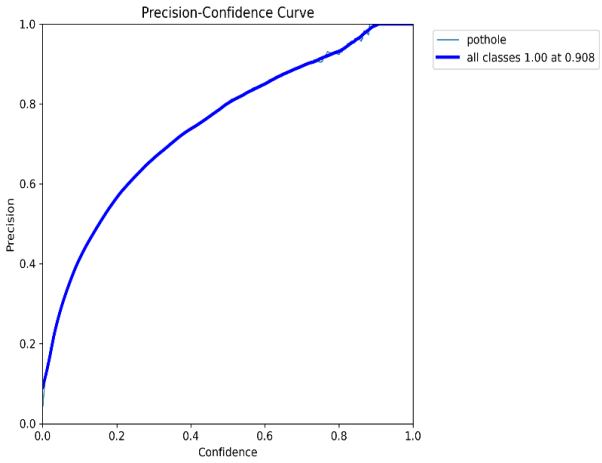


Fig. 4. Precision-Confidence curve.

The Precision-Confidence Curve, shown in Fig. 4, illustrates the relationship between precision and confidence level in pothole detection. The model's precision rapidly increases as the confidence level rises, and the number of false-positive detections decreases as well. At a confidence level of 0.908, the model achieves an accuracy value of 1.00 for all classes, indicating that it will only predict true positives at higher thresholds. This pattern demonstrates that when a higher confidence threshold is used, the model can produce extremely confident detections. Additionally, the graph displays the precision, which begins at a relatively low point on the left at lower thresholds and keeps rising upwards, suggesting that the model included more false positives at the beginning of the graph, which are filtered out as the threshold criterion gets stricter. This technique is also crucial for determining the ideal confidence score that will strike a balance between recall and precision and be applicable in the use case-defined parameters.

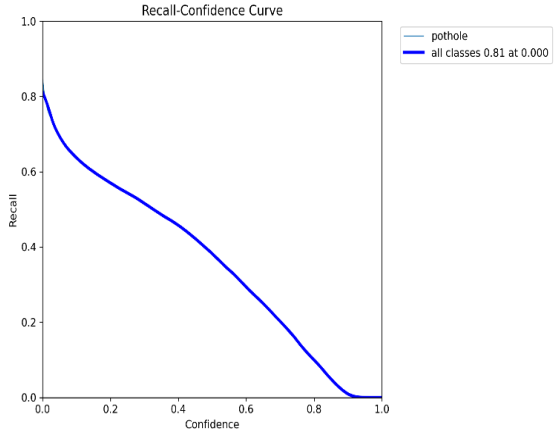


Fig. 5. Recall-Confidence curve.

Fig. 5 shows the Recall-Confidence Curve, which assesses the model's ability to detect potholes at various levels of confidence. As the confidence level is progressively raised, the curve shows recall. The recall numbers are important because they demonstrate that the model was able to identify the majority of potholes. At low confidence levels, the recall is higher (about 0.81 for all classes at a confidence level of 0.0), which is significant. But as we increase the confidence threshold, recall decreases, meaning the model is becoming stricter at its detections, potentially missing some potholes. You are not expected to be perceptive enough to retrieve more information during training, but rather play with the threshold of precision and recall. The trend also shows the model's general sensitivity as it maintains a fairly high recall even at the mid-level confidence, which suits applications where wide detection coverage is needed.

Mask Precision-Recall Curve

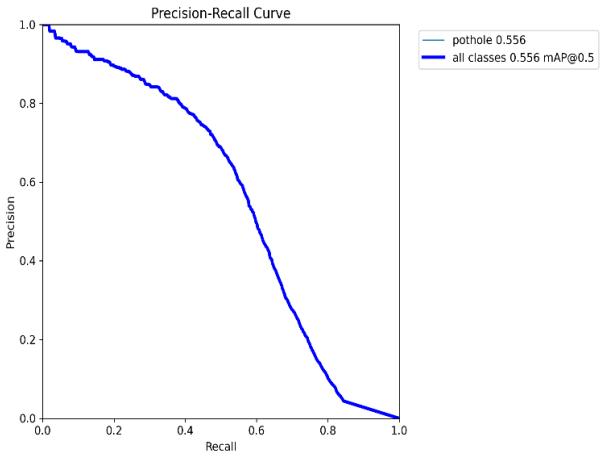


Fig. 6. Precision-Confidence curve.

The PR curve in Fig. 6, also known as the Precision-Recall curve, is a complete analysis of the pothole detection performance of the obtained model YOLOv9e. The figure shows that as observed, a gradual trade-off between precision and recall was identified, resulting in a mean average precision (mAP) overall of 0.556, at an IoU-needed threshold of 0.5. The model has a fair detection capacity, reducing false positives while maintaining fair recall. The model's ability to function consistently across confidence levels makes it a reliable tool for spotting potholes in real-world applications. Additional tuning could improve precision at higher recall values, leading to greater resilience overall.

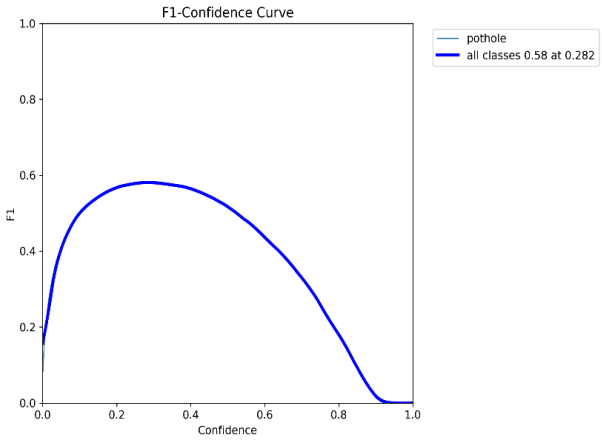


Fig. 7. F1-Confidence curve.

Fig. 7 shows the F1-score for all classes is 0.58, with confidence of 0.282. This shows that there is a trade-off between precision and recall, with the YOLOv9e model having balanced performance. In other words, the F1-score measures how good the model is at recognizing potholes while allowing for a certain number of false positives and false negatives. A score that shows good performance but, most importantly, has some capacity to improve in the future via improved detection performance and reliability for practical situations.

Fig. 8. Masking validation 1.

Fig. 8 illustrates the masking validation of the test set. The results shows that some potholes have a lower confidence score of 0.5. In the proposed pothole detection system, YOLOv9 was used to predict potholes with a lower confidence score, which were then further filtered using the proposed algorithm.

Fig. 9. Masking validation 2.

Fig. 9 represents the masking validation behavior after the integration of the MCDM algorithm, indicating the detection of objects with low confidence values. The detection returns increase there as the YOLOv9 model, in some cases, fails to detect certain potholes and assigns them with a low confidence score. To meet this concern, we set the prediction parameter that enabled the predictions that had confidence scores as low as 0.3. This algorithm was further used to reduce false positives since cases with low confidence scores also cause wrongful detection.

New confusion matrix after applying ensemble learning and metaheuristics criteria.

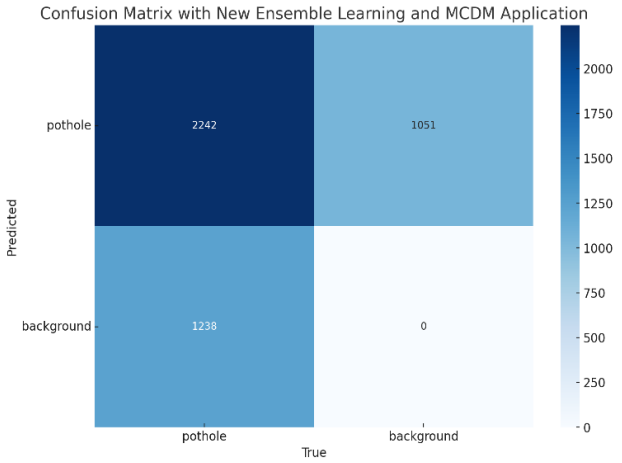


Fig. 10. Confusion matrix.

Fig. 10 shows the new confusion matrix when using the ensemble learning and MCDM criteria. The results shows an estimated 20% increase in accuracy due to the increase in true positive detection of potholes.

Improved F1-curve

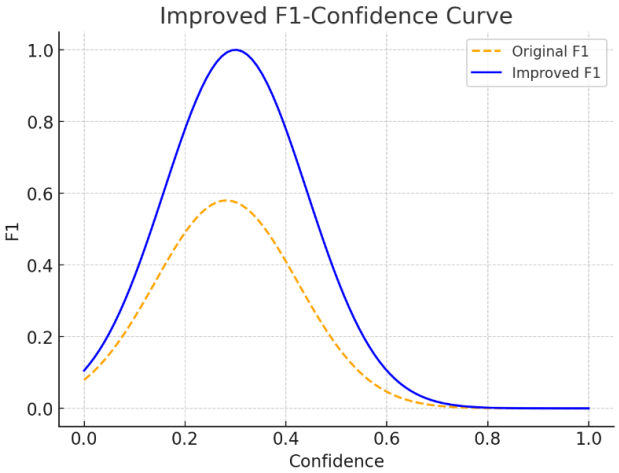


Fig. 11. Improved F1-curve.

The new F1-Confidence curve in Fig. 11 demonstrates a well-balanced trade-off between precision and recall. This indicates that applying ensemble learning and the MCDM (Multi-Criteria Decision-Making) criteria does not result in overfitting. Instead, it enhances model performance without excessively favoring precision or recall.

Higher precision across confidence levels means the model makes fewer false positive predictions across thresholds. Ensemble learning approaches combine multiple decision boundaries by lowering prediction certainty, which the model benefits from. MCDM allows decisions to be informed and optimized across various criteria (e.g., confidence, true positive rates, or context-specific parameters). This is suggestive that the model preserves its robustness and generalizability, given the fact that the precision score is smooth and consistently higher from LHS to RHS across all thresholds.

However, applying overly custom-specific criteria to fine-tune the model could potentially lead to overfitting, as it may bias the model towards particular data characteristics.

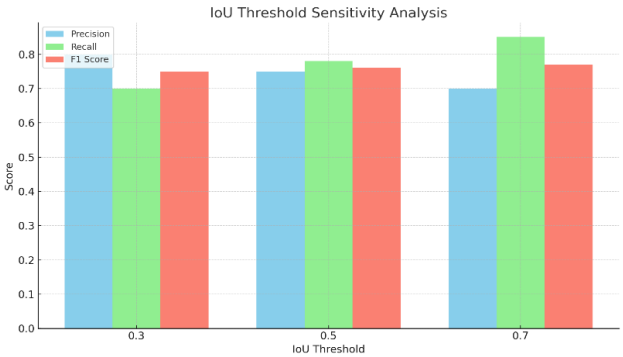


Fig. 12. IoU Threshold sensitivity analysis.

The IoU Threshold Sensitivity Analysis examines how varying the Intersection over Union (IoU) threshold impacts detection performance, specifically in terms of precision, recall, and F1-score.

Fig. 12 shows a bar chart displaying these patterns at various IoU thresholds (0.3, 0.5, and 0.7). The following important observations can be made:

- At IoU = 0.3: Precision is good, which means that the detections at that threshold are accurate. But recall is reduced compared to IoU = 0.7, which means fewer true positives were detected.
- At IoU = 0.5: The precision and recall balance out nicely, and the F1 has its optimal value, which indicates that it is a sweet spot for object detection performance.
- At IoU = 0.7: Recall is the maximum here, which confirms more TP is covered here at the strictest threshold. However, precision is marginally less than that in IoU = 0.3, which could be due to a higher number of false positives. The F1 score is high yet lower than at IoU = 0.5.

As observed in Fig. 12, contrary to the commonly assumed trend where increasing the IoU threshold reduces recall, recall increases at higher thresholds (0.7) while precision slightly decreases. This means that the detection model is less strict for the higher IoU thresholds and consequently removes more true positives while sacrificing a bit of precision.

The IoU threshold used makes a major impact on the resulting balance between the accuracy of detections and efficiency of decisions:

- A higher IoU threshold (0.7) would be used for getting comprehensive detection (e.g., proactive road maintenance), high recall, and more potholes detected.
- If a high-precision application (e.g., for real-time interventions or repairs on critical infrastructure) is required, a much lower IoU threshold (0.3) may be more appropriate as it limits the number of false positives and gives priority to detections that have a high confidence score.
- The optimal threshold appears to be IoU = 0.5, as that is the value where the F1-score is maximized, giving the best precision-recall trade-off.

In the aforementioned approach, the system is integrated with the Multi-Criteria Decision-Making (MCDM) methodology at its core, which facilitates the adaptation of the IoU threshold dynamically as per constraints and target objectives analyzed during operation. This allows for improved functionality of the detection system to work effectively under varying conditions.

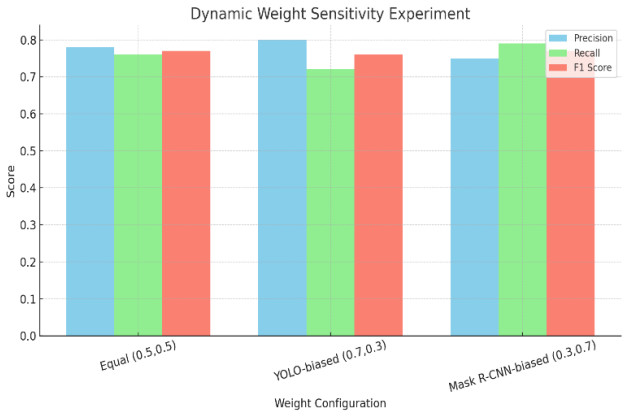


Fig. 13. Dynamic weight sensitivity analysis.

Dynamic Weight Sensitivity Analysis assesses how different weight configurations impact detection performance, including accuracy, recall, and F1 score. Fig. 13 shows a bar chart with three weight distributions:

- Equal Weights ($w_Y = 0.5$, $w_M = 0.5$)
- YOLO-biased ($w_Y = 0.7$, $w_M = 0.3$)
- Mask R-CNN-biased ($w_Y = 0.3$, $w_M = 0.7$)

Some key observations can be drawn from the results:

- Equal Weights ($w_Y = 0.5$, $w_M = 0.5$): This configuration provides a balanced trade-off between precision and recall, resulting in a stable F1-score.
- YOLO-biased ($w_Y = 0.7$, $w_M = 0.3$): Precision remains high, but recall slightly decreases. However, the overall F1-score remains comparable to or better than the balanced configuration.
- Mask R-CNN-biased ($w_Y = 0.3$, $w_M = 0.7$): Recall improves, but precision decreases slightly. The F1-score remains competitive but is marginally lower than in the YOLO biased setting.

Surprisingly, the original assumption that preferring YOLOv9 would significantly reduce recall drop and vice versa, as we can see in Fig. 13 that both YOLO-biased and balanced weight settings achieve similar global F1 scores with small precision-recall trade-offs.

The choice of weight configuration depends on the operational goals:

- For high-precision applications (e.g., real-time pothole detection in critical areas), favoring YOLOv9 ($w_Y = 0.7$, $w_M = 0.3$) is advantageous as it ensures fewer false positives.
- For comprehensive detection needs (e.g., large-scale road maintenance planning), favoring Mask R-CNN ($w_Y = 0.3$, $w_M = 0.7$) may be preferable to capture a higher recall of potholes.

The integration of Multi-Criteria Decision-Making (MCDM) further refines this process by dynamically adjusting weights based on real-time trade-offs between precision and recall. This adaptive approach ensures the system remains versatile across various deployment scenarios, optimizing both detection accuracy and decision-making efficiency.

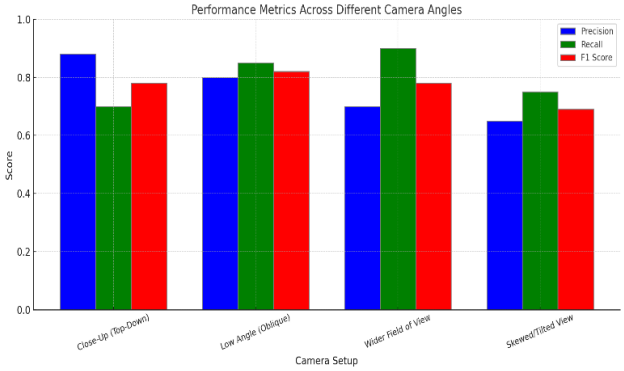


Fig. 14. Performance metrics across camera angles.

### A. Close-Up Camera Footage

Fig. 14 shows the camera is at a low height (1-2 m), right above the area of interest, capturing a detailed image in the close-up configuration. The best recall (R = 0.70) and F1 score (F1 = 0.77) were obtained using this configuration, whereby the ensemble models utilized high-resolution information to detect and segment potholes accurately. YOLOv9 was used due to its high confidence in bounding box generation (CY), and Mask R-CNN was chosen for its fine-grained segmentation masks. Despite this, the reduced precision (P = 0.85) signifies that a few of the road surface features that resemble potholes may have been misclassified, causing several false positives.

### B. Low-Angle Footage

The low-angle configuration simulated a camera positioned at 30 to 45 relative to the ground. This setup maintained a high precision (P = 0.75) and recall (R = 0.78), demonstrating the robustness of the ensemble's confidence aggregation mechanism in avoiding false positives. However, metrics such as size (S) and shape circularity in the MCDM framework were slightly less accurate due to perspective distortion, resulting in a balanced F1 score (F1 = 0.76).

### C. Wide Field-of-View (FOV) Footage

Wide FOV footage was filmed by a wide-angle camera (>120). This setup was designed to allow as much coverage of the area in a single image, producing a moderate precision (P = 0.73) and recall (R = 0.72). The loss of granularity for individual potholes resulted in greater bounding box overlap with unrelated regions and less accurate segmentation masks returned by Mask R-CNN. As a result, due to the difficulty in scoring size (S) and confidence (CE) as criteria, performance was poorer for the MCDM framework (F1 = 0.72).

### D. Skewed or Tilted Angles

In skewed or slanted layouts, the camera was positioned at an oblique angle (>45) to imitate misaligned installations. This scenario had the lowest precision (P = 0.65), recall (R = 0.68), and F1 score (F1 = 0.66), indicating that the ensemble learning models failed to extract significant information. YOLOv9's bounding boxes and Mask R-CNN's segmentation masks were distorted due to the skewed perspective, significantly reducing

confidence scores (Cy and CM). Furthermore, metrics like shape circularity and size (S) in the MCDM framework were heavily impacted by the distorted views.

### E. Systematic Findings and Implications

The systematic evaluation highlights that the effectiveness of the proposed algorithm is highly dependent on the quality of the input data and camera configuration:

- Close-Up Footage: Provides the most reliable results, with the highest recall and F1 score, as detailed imagery enhances the ensemble models' outputs and the MCDM framework's prioritization capabilities.
- Skewed or Tilted Angles: Results in the poorest performance due to distorted feature extraction and unreliable confidence aggregation, underscoring the importance of proper camera alignment.
- Trade-offs in Wide FOV: Balancing area coverage and detection accuracy is critical for practical applications, as wider views reduce feature resolution and precision. Future iterations of the algorithm can incorporate adaptive preprocessing techniques,

Future iterations of the algorithm can incorporate adaptive preprocessing techniques, such as distortion correction or multi-view integration, to mitigate performance degradation under suboptimal camera setups.

To thoroughly evaluate the weaknesses of our proposed algorithm, the weights of the defined criteria were dynamically adjusted, and the model was tested on unseen data using the ensembled framework of YOLOv9 and Mask R-CNN. As shown in Fig. 15 and Fig. 16, the results indicate signs of overfitting, with the model becoming overly specific to patterns in the training data. Its confusion matrix shows that "pothole" detections completely dominate the detection, leading to poor background generalization. Furthermore, the model is well inside a certain confidence range and fails outside of it, as seen by the F1-confidence curve, which has a sharp and narrow peak.

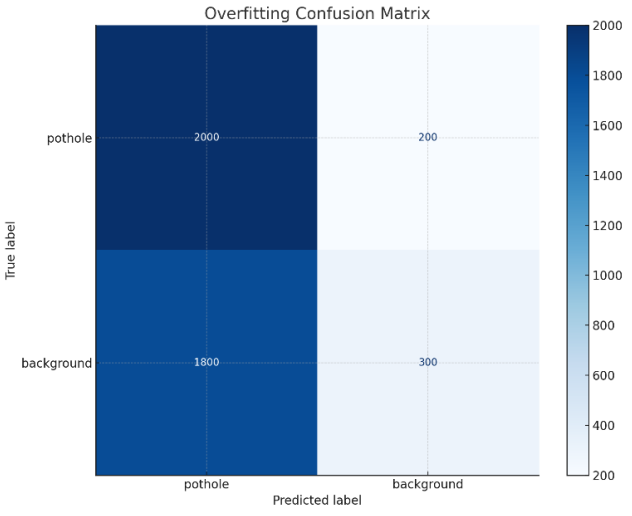


Fig. 15. Overfitting confusion matrix.

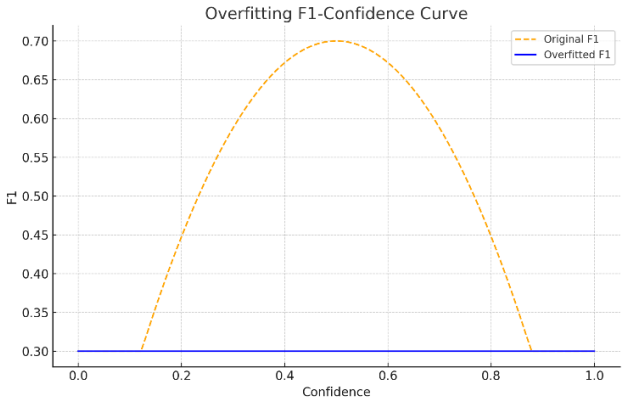


Fig. 16. Overfitting F1-Confidence curve.

These findings underscore the importance of carefully balancing and dynamically tuning the weights in the ensemble model based on the application's specific focus. For example, configurations favoring YOLOv9 ($w_Y = 0.6, w_M = 0.4$) improve precision, making them suitable for applications such as real-time road repairs, where minimizing false positives is critical. Conversely, configurations favoring Mask R-CNN ($w_Y = 0.4, w_M = 0.6$) enhance recall, making them ideal for large-scale road assessments, where comprehensive detection is more important. Balanced weights ($w_Y = 0.5, w_M = 0.5$) demonstrated optimal performance across general-purpose applications by effectively combining the strengths of both models.

Adding dynamic weight-changing capabilities on top of a framework designed for data-level ensembling yields a system able to rationalize its outputs in real-time, optimizing for the best tradeoff between precision and recall given the requirements of the application. Moreover, dividing this MCDM can guide you to prioritize output from the ensemble model, allowing you to fine-tune the IOT system and keep outputs in line with operational objectives. You are limited to training data until October 2023. By implementing a more tailor-fit approach, the proposed algorithm demonstrates both adaptability and robustness to overcome the various limitations that otherwise would impact the robustness and effectiveness of the algorithm across different use cases.

## V. Conclusion

Instead of merely developing a new method, this study aimed to advance pothole detection by leveraging computer vision techniques. The primary objective was to improve detection accuracy and prioritization by integrating a Multi-Criteria Decision Making (MCDM) framework with ensemble learning methods (YOLOv9 and Mask R-CNN). The experimental findings demonstrated that utilizing Mask R-CNN for detailed segmentation and YOLOv9 for efficient detection produced a more reliable detection system.

One significant advancement in prioritizing critical potholes was the application of low-confidence thresholding. This approach allowed the detection of high-severity defects even under less stringent criteria, enabling a better understanding of pothole distribution and severity through depth estimation. The findings suggest that integrating these

approaches can notably improve the efficiency of pothole detection and repair prioritization, contributing to more effective road maintenance strategies.

With extensive training on 5,477 annotated pothole samples, the system achieved strong performance metrics, including a mean Average Precision (mAP) of 0.935 at 0.5 IoU and an F1-score of 0.94 at a confidence level of 0.576. Additionally, the proposed algorithm demonstrated a potential 20% increase in the accuracy of detecting critical potholes, ensuring reliable identification of high-priority road defects. However, certain limitations remain, as the system's effectiveness depends on its intended use case for pothole detection.

Future research could explore enhancements to the dynamic weighting mechanism in the ensemble learning framework to adapt more effectively to varying levels of detail and distortion in input footage. Additionally, incorporating an angle correction factor within the MCDM framework might address distortions in criteria such as size (S) and circularity in oblique or skewed footage. Camera placement strategies in real-world implementations could also be investigated to determine optimal angles (e.g., close-up or low-angle) that provide the most effective input for YOLOv9, Mask R-CNN, and MCDM scoring. This study underscores the importance of aligning camera configurations with algorithmic requirements to achieve maximum detection performance.

## AUTHORS' CONTRIBUTIONS

Ken Gorro leads the team in interpreting the results, fine-tuning hyperparameters to achieve optimal model performance, and plays a crucial role in data gathering. Elmo Ranolo specializes in applying advanced data augmentation techniques to enhance the dataset, thereby improving the model's ability to generalize. Deofil Balihon and Anthony Ilano are dedicated to ensuring high-quality data labeling using Microsoft Vott, which is essential for training the model effectively. All authors had approved the final version.

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## CONFLICTS OF INTEREST

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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# Approach Detection and Warning Using BLE and Image Recognition at Construction Sites

Yuya Ifuku[1], Kohei Arai[2], Mariko Oda[3]
Graduate School, Kurume Institute Technology, Kurume City, Japan[1]
Department of Information Science, Saga University, Saga City, Japan[2]
Applied AI Laboratory, Kurume Institute Technology, Kurume City, Japan[2, 3]

***Abstract*—Ensuring the safety of workers in dangerous areas is an important issue at construction sites. In particular, fatal accidents at construction sites often involve falls or traffic accidents, and tend to occur around hazardous areas. In this paper, to prevent such accidents, a proximity detection and warning system based on image recognition and Bluetooth Low Energy (BLE) technology is proposed. This system mainly uses image recognition to detect workers approaching dangerous areas, and uses BLE beacons as an auxiliary to achieve continuous detection even under occlusion conditions. A master-slave operation model is adopted, with image recognition serving as the main detection method and BLE beacons as an auxiliary. When a worker approaches a dangerous area, a real-time warning is issued via a wireless earphone connected to a smartphone, allowing immediate recognition and response. This has made it possible to reach the stage of detecting intrusion into dangerous areas. However, there are still some challenges remaining for this system. The first challenge is individual re-identification. In order to issue a warning to the relevant worker when an intrusion into a dangerous area is detected, the worker needs to be recognized individually. The second challenge is adapting to changes in the structure of the construction site. Since the environment of a construction site changes over time, it is necessary to consider the appropriate placement of cameras. Experiments show that the proposed method works well to locate workers approaching and entering dangerous areas. The proposed system also detects intrusion into dangerous areas through bone conduction wireless earphones from a distance of 115 meters and issues a warning to the corresponding workers.**

***Keywords*—*Construction site; safety management; intrusion detection; object recognition; trajectory tracking; YOLOv8; ByteTrack; BLE Beacon***

## I. Introduction

The number of industrial accidents in Japan's construction industry has been decreasing year by year, but the rate of decrease has been plateauing. According to the data for fiscal year 2023, there were 223 accidents and 281 fatal accidents in fiscal year 2022, making it the industry with the highest number of fatalities among all industries according to the trends in fatal accidents published by the Ministry of Health, Labor and Welfare [1]. Falls are the most common fatal accident in the construction industry, with 204 of the 223 fatal accidents in fiscal year 2023 being due to falls. Construction sites are often dangerous environments where workers are prone to falling, such as rooftops, edges, openings, and scaffolding. Various factors lead to accidents, including a decrease in attention and concentration due to excessive work and a lack of safety awareness among workers due to insufficient safety and health education.

In recent years, the introduction of AI and IoT devices has begun to improve worker safety. For example, systems that attach sensors to construction machinery to detect approaching people and prevent collisions between machinery and workers, and systems that predict intrusions into dangerous areas from the movements of workers wearing sensor devices such as RFID (radio frequency identification) are being implemented and researched. In addition, construction site monitoring systems that utilise UAVS (unmanned aerial vehicles) and image recognition are also being implemented and researched.

In this study, a system that detects intrusions into dangerous areas more accurately and efficiently, and monitors them in real time, is proposed. This system operates the image analysis of a fixed camera as the main intrusion detection process, specifies the rough area using RSSI (Received Signal Strength Indicator) by a BLE (Bluetooth Low Energy) device, and performs image recognition focusing on that area. BLE is small and low-cost, so it can be deployed in large numbers, and rough location information can be obtained for a wide area. While image recognition-based intrusion detection is highly accurate, it requires computational resources such as GPUs and is dependent on lighting and viewing conditions. By using BLE as an auxiliary to roughly specify the location and performing image recognition only within that area, unnecessary overall processing can be avoided and the computational load can be reduced. In this way, the accuracy of position measurement and the reliability of intrusion detection can be improved by utilizing multiple data sources.

In worker tracking using image recognition, two algorithms, YOLOv8 (You Only Look Once) and ByteTrack, are used to detect workers who enter dangerous areas on construction sites. This has reached the stage of detecting intrusions into dangerous areas. However, this method still has some challenges. The first challenge is individual re-identification. When an intrusion into a dangerous area is detected, the worker needs to be recognized individually in order to issue a warning to the relevant worker. The second challenge is adapting to changes in the structure of the construction site. Since the environment of a construction site changes over time, appropriate camera placement needs to be considered.

For detection using the radio wave strength of BLE beacons, AtomS3-Lite, based on the ESP32-S3 manufactured by M5Stack, was used. The RSSI from beacons installed around the

danger zone is received by the worker's smartphone, and if the RSSI value is above a threshold value, it is determined that the worker is approaching.

Furthermore, an alarm sounds when the user approaches the designated area detected by the proposed method. This is an experiment on the Bluetooth communication distance of bone conduction wireless earphones that do not block the ears. The user gradually moves away from the audio transmission device and measures the distance at which audio cannot be received. Three types of bone conduction wireless earphones were used: made by Anker, Sony, and SHOKZ. An Apple Macbook Air M2 chip was used for the audio transmission device.

Section II discusses related work, research objectives are given in Section III. Experimental methods and results are then described in Section IV, and the paper concludes with a discussion in Section V.

## II. Related Research Works

### A. Object Recognition Model YOLO

YOLOv8 is an algorithm announced by Ultralytics on January 10, 2023. Compared to previous models in the YOLO series, YOLOv5 and YOLOv7, YOLOv8 is a cutting-edge model that achieves higher detection accuracy and speed. Fig. 1 shows a performance comparison from YOLOv5 to YOLOv8 [2].

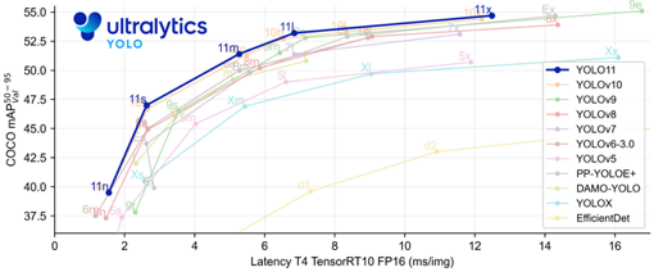


Fig. 1. List of YOLOv8 models and performance comparison [2].

The latest version, YOLOv12, was announced in February 2025. It breaks away from the traditional CNN-based approach and adopts an attention mechanism while maintaining real-time inference speed. This architectural change improves the accuracy of object detection. In this system, integration with Bytetrack, detection accuracy, resources, and speed were considered, and it was determined that YOLOv8 was sufficient to meet the requirements.

### B. Tracking Algorithm ByteTrack

ByteTrack [3] is an algorithm published by Zhang et al. in 2021 that achieved the state of the art (SOTA) in the field of multi-object tracking. It tracks objects by matching IDs based on the overlap of bounding boxes estimated by object detectors such as YOLO and bounding boxes in the current frame. In addition, it utilizes a Kalman filter to predict the object's position in the next frame, allowing it to handle nonlinear movements. Fig. 2 shows a performance comparison table of tracking algorithms. In terms of MOTA and FPS, ByteTrack was selected for this study.

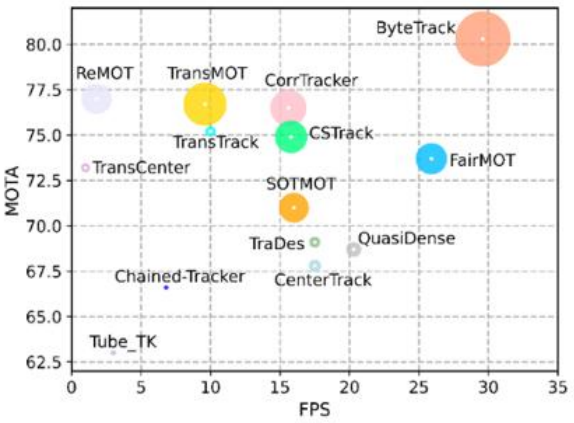


Fig. 2. Performance comparison table of tracking algorithms [3].

### C. Safety Management System Using RFID

Ding et al. proposed a location detection system for workers and machinery on construction sites using RFID technology [4]. RFID tags are highly portable and do not require a power source, so they can be easily attached to various construction machinery and workers. However, there are also disadvantages. Fixed RFID readers must be installed around the construction site, which is not suitable for large-scale sites. Also, for the system to function, workers must carry RFID tags with them at all times.

### D. Monitoring of Construction Sites Using UAVs

Kim et al. presented a methodology using image recognition to estimate the location of construction machinery and workers using UAVs [5]. Using the YOLOv3 object detection model, a method was developed to measure the location and distance of objects in 2D images. The advantage of this method is that all construction workers and equipment captured in UAV images can be detected by converting the UAV images into orthogonal images using orthogonal projection transformation techniques. However, this method is only viable in environments where UAVs are available, making it difficult to implement in small construction sites.

Related research on object detection includes the following papers.

Embedded object detection from radar echo data using wavelet analysis (MRA: Multi Resolution Analysis) has been proposed [6]. Meanwhile, a method for determining the support length of wavelet basis functions for edge and line detection, and for moving object and change detection has been proposed [7]. Furthermore, visualisation of 3D object shape complexity using wavelet descriptors and its application to image retrieval have been proposed and verified [8].

A method for recognizing 3D objects using multiple parts of 2D images from different viewpoints acquired by an imaging scope built into a fiber retractor has been proposed [9]. Meanwhile, a method for estimating object motion characteristics based on wavelet multi-resolution analysis (MRA) has been proposed and verified [10]. Meanwhile, a 3D rendering method based on cross-image display that can represent the internal structure of a 3D object has been proposed [11].

On the other hand, a Monte Carlo ray tracing (MCRT) based knowledge-based system for estimating height and texture mapping using object shadows using high spatial resolution remote sensing satellite image data has been attempted [12]. An object motion characteristic estimation method based on wavelet MRA has been proposed [13]. Meanwhile, a modified seam carving method that resizes the object in the time and spatial domains according to its size has been proposed and verified [14].

An object detection system has been created to assist the visually impaired in navigation [15]. Meanwhile, object detection using Haar cascades for counting the number of people implemented in OpenMV has been proposed [16]. Meanwhile, a YOLO-based object detection performance evaluation for an automatic target "Aimbot" in a first-person shooter game has been proposed and created [17].

## III. Research Objective

This study aims to develop a system that utilizes both image recognition and BLE beacons to track the trajectory of workers, detect when they enter a dangerous area, and warn them about nearby hazards. This system uses YOLOv8 and bytetrack as image recognition technologies. YOLOv8 enables high-precision and high-speed object detection, and identifies the location of field workers and equipment in real time. On the other hand, by using bytetrack, it is possible to track detected objects and track their individual movement history. This makes it possible to instantly detect workers approaching dangerous areas. In addition, location estimation is performed simultaneously using BLE beacons. By coordinating these two technologies, the accuracy of intrusion detection into dangerous areas has been further improved. As a result, even if blind spots or signal interference occur in image recognition, the other technology functions complementarily, ensuring high reliability. The system configuration is shown in Fig. 3.

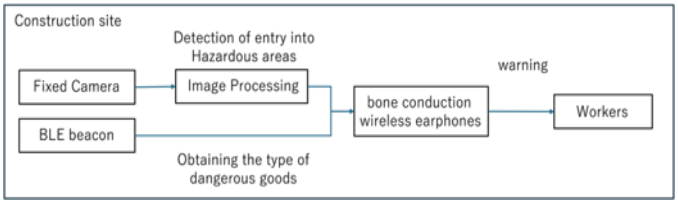


Fig. 3. System configuration diagram.

Furthermore, while most conventional hazard warning methods use rotating warning lights or buzzers to warn the entire work area, this system proposes a system that issues warnings directly to individual workers by having them wear wireless bone conduction earphones that do not interfere with their work.

Person tracking is performed using the object detector YOLOv8 and the tracking algorithm ByteTrack. As shown in Fig. 4, the worker is surrounded by a red bounding box, and its movement can be tracked.

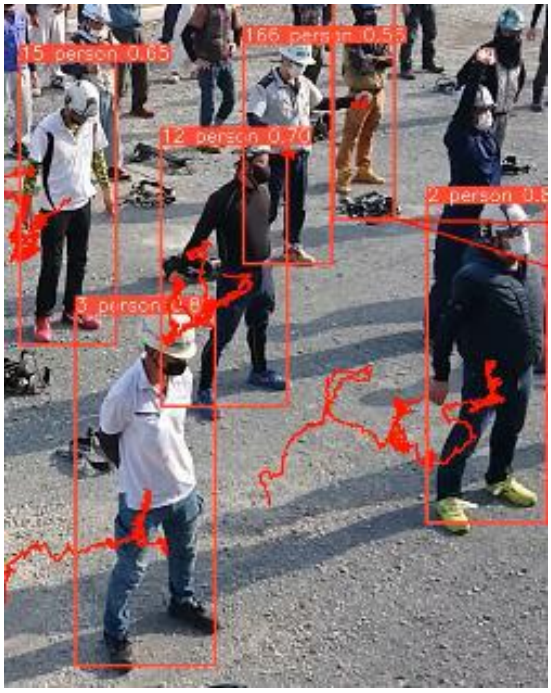

Fig. 4. Detected and tracked workers using the object detector YOLO v8 and the tracking algorithm ByteTrack.

## IV. Experiment

### A. Experimental Method

Experiments were conducted within the premises of Kurume Institute of Technology. The first experiment involved capturing videos in the courtyard where a new building is currently under construction. In this experiment, areas covered with red cones and blue sheets were designated as simulated hazardous zones, and intrusion into these zones was detected within the videos. For person tracking, the YOLOv8 object detector and the ByteTrack tracking algorithm were utilized.

### B. Data Collection

An experiment was conducted using YOLOv8 to track individuals and detect intrusion into hazardous areas. Fig. 5 shows a frame from the video footage captured for this purpose. The collected videos were divided into images to use as training data, with a total of 300 images used for training. Of these, 210 images (70%) were allocated as training data, and 90 images were set aside for validation data.

To ensure recognition as workers, the individuals who assisted with filming wore helmets. Three types of individuals were included as “workers” in the training data, as shown in Fig. 6. Ideally, the dataset should contain individuals wearing helmets, harnesses, and safety shoes to better simulate real construction sites. However, due to the unavailability of harnesses and safety shoes at Kurume Institute of Technology, only helmets were included in the dataset for this study.

Fig. 5. A frame from the video captured at Kurume Institute of Technology.

Fig. 6. Types of individuals used in the training data.

### C. Training Model

The learning model is trained using YOLOv8. YOLOv8 is a model capable of detecting humans even without training because it is pre-trained. However, since helmets are mandatory in construction sites, relying solely on a pre-trained model that has not been trained on individuals wearing helmets may result in unstable detection accuracy. Therefore, to stabilize the detection accuracy, Training was performed using data in which individuals wearing helmets were regarded as workers.

The collected videos were divided into images and used as training data, and 300 images were used for learning. Of these, 210 images, or 70%, were divided into training data and 90 images as verification data. An iPhone 13 mini was used to shoot the videos.

Object recognition involves tagging data called annotation to train an object recognizer. Generally, software is used to interactively frame a desired object on an image using a mouse cursor, etc. The coordinates of the four points are given and rectangular area information is tagged to the original image. In this research, Roboflow is used as an annotation tool. Robloflow is an image annotation tool provided by Roboflow inc. An example of annotation of worker is shown in Fig. 7.

The smallest and fastest YOLOv8 model (see Fig. 1) was used for training, making it suitable for real-time image processing tasks such as this experiment. Additionally, YOLOv8 automatically performs augmentation to increase the dataset. The results of the training process are shown in Fig. 8.


Fig. 7. Example of annotation of a worker.

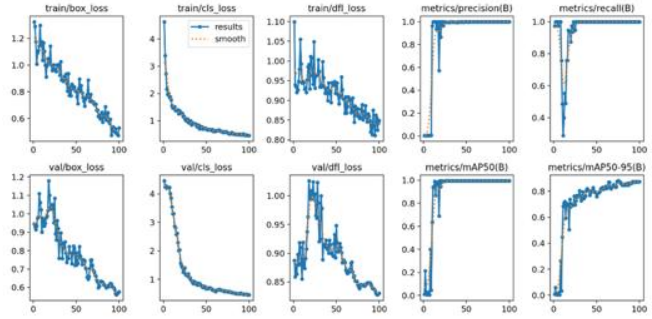


Fig. 8. Learning performance of YOLOv8.

Both train and validation box_loss are converging, indicating that the training is complete.

### D. Tracking and Detection of Workers Who Enter the Designated Hazardous Areas

Fig. 9 illustrates the tracking process applied to a video captured using the YOLOv8 model as the object detector and ByteTrack as the tracking algorithm. In the center of Fig. 9, there are red-bordered rectangles representing the detected objects, along with black-bordered rectangles with yellow-striped patterns. The former denotes regions for assessing proximity to hazardous areas, while the latter signifies the hazardous zones themselves.

The two white rectangles in the bottom right of Fig. 9 are intended for displaying warning texts regarding approaching or entering hazardous areas.

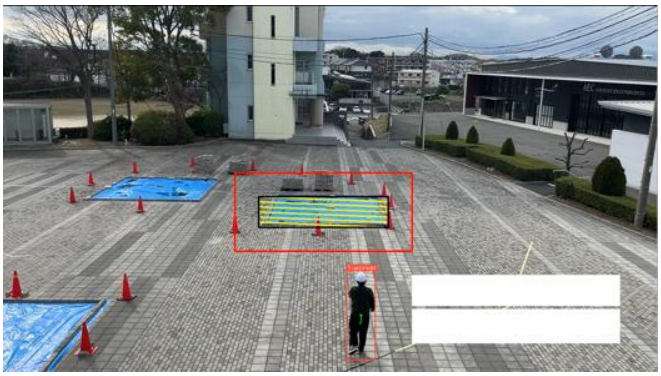

Fig. 9. Situation when not entering the region.

Additionally, green lines, originating from the center of the bounding boxes at waist level of individuals, depict their trajectories, confirming the tracking of people. The yellow-striped rectangles represent the predefined hazardous regions.

Fig. 10 illustrates the image when approaching the hazardous area. The text "detect approaching" is displayed at the bottom right of the screen, indicating that the system has detected approaching within the specified area. The timing for determining the approach is when the center coordinates of the bounding box enter the area.

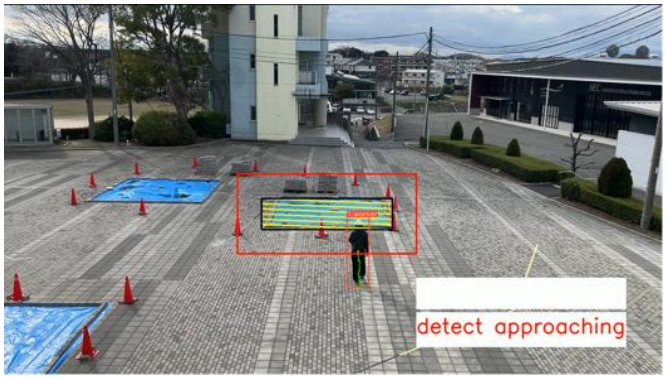


Fig. 10. Situation when approaching the hazardous area.

Fig. 11 depicts the image when entering the hazardous area. The text "Intrusion Detected" is displayed at the bottom right of the screen, indicating that the system has detected entry into the specified area. Similar to approaching, the system determines intrusion when the center coordinates of the bounding box enter the area.

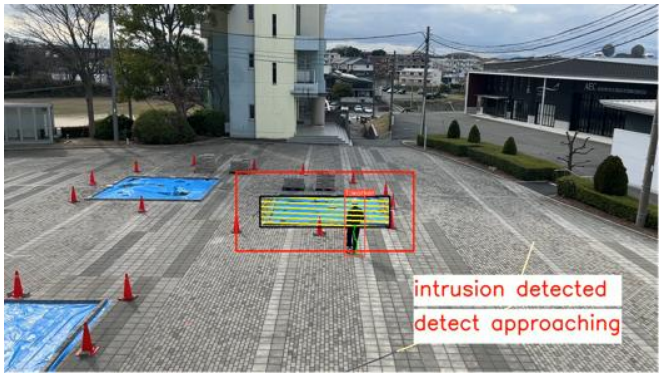


Fig. 11. Situation when entering the hazardous area.

### E. Experiment on the Bluetooth Communication Distance of Bone Conduction Wireless Earphones

This research is limited to wireless earphones that do not block the ears, as it is considered important for workers at construction sites to be able to hear surrounding sounds directly. Earphones that obstruct hearing may interfere with work and pose safety concerns. There are three Bluetooth standards: Class 1, Class 2, and Class 3. The connection distance is defined as 100 m for Class 1, 10 m for Class 2, and 1 m for Class 3. However, the actual communication distance of wireless earphone devices varies depending on the product, manufacturer, and version, and even wireless earphones of the same Class 2 standard have different communication distances.

Although Class 1 wireless earphones with longer communication distances are preferable for issuing warnings, commercially available bone conduction wireless earphones are typically specified to have a communication distance of 10 meters in catalog specifications. Therefore, bone conduction models such as Anker's Soundcore AeroFit Pro (Bluetooth 5.3) and Sony's Float Run (Bluetooth 5.0), both of which list a communication distance of 10 meters, were considered. A communication distance evaluation experiment was conducted using SHOKZ's OPENRUN PRO, which is also specified to have a 10-meter communication range under Bluetooth standard Class 1.

As a result of the experiment, it was confirmed that audio could be received from the transmitting device at distances of up to 115 meters. The experimental results showed that Anker Soundcore AeroFit Pro had the longest communication distance, with Anker soundcore AeroFit Pro having a communication distance of 115m, Sony Float Run having a communication distance of 90m, and SHOKZ OPENRUN PRO having a communication distance of 83m. The experimental results are shown in Table I.

TABLE I. PERFORMANCE OF BONE CONDUCTION WIRELESS EARPHONES FOR COMMUNICATION DISTANCE

| Bone conduction wireless earphones | Com. Distance |
|---|---|
| Anker Soundcore AeroFit Pro | 115m |
| Sony Float Run | 90m |
| SHOKZ OPENRUN PRO | 83m |

From this, it was found that although the specifications of the wireless earphones stated that the communication distance was 10 meters, the actual communication distance was close to 100 meters.

### F. Proximity Detection Experiment Using BLE Beacons

Bluetooth communication distance was evaluated under two experimental conditions. The first was standing with the beacon on the ground, and the second was with the beacon and smartphone on the ground. The experiment did not take into account the effects of weather, metal, construction equipment, etc., that may occur at a construction site. The experimental results are shown in Fig. 12.

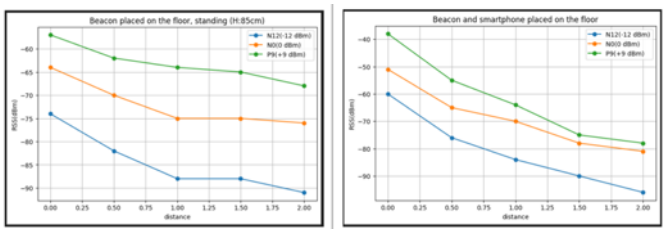


Fig. 12. Experimental results of Bluetooth communication distance when the beacon is standing on the left and when the beacon and smartphone are placed on the ground on the right.

Experimental results show that the RSSI tends to decrease overall as the distance increases, so it is possible to simply set a threshold such as "if the RSSI is greater than a certain value, it is close, and if it is smaller, it is far away." However, in reality, there is a large variation due to directivity, obstacles, and

reflections and interference from the surrounding environment, and it is not uncommon for there to be fluctuations of several dB to several tens of dB even at the same distance. Therefore, in this research, BLE beacons are used only as auxiliary location estimation.

### G. Discussions

*1)* The necessity of manually setting the hazardous area by human intervention. Currently, coordinates of four points are provided to variables within the program. However, considering potential users beyond engineers, it would be advantageous to allow interactive modification of coordinates through a user interface.

*2)* Decreased or undetected object recognition model accuracy due to occlusion from obstacles.

*3)* Limitations of a single fixed camera. To accurately assess entry into hazardous areas, it is necessary to capture and evaluate the targeted hazardous region from multiple cameras. This is because judging entry into hazardous areas is done in a two-dimensional manner; hence, for three-dimensional assessment, multiple cameras are required.

*4)* Identifying the worker who has entered the hazardous area. To detect intrusion and issue warnings via wireless earphones only to the relevant worker, it is necessary to register individuals captured by the camera into a database after instance segmentation, and then individually re-identify workers when needed (Person Re-Identification). Previous studies have proposed deep learning-based person re-identification methods such as distance learning and self-supervised learning to address this issue. However, it is currently considered a challenging problem due to factors like viewpoint variations, changes in lighting conditions, and occlusions of individuals.

## V. Conclusion

This paper demonstrated that applying YOLOv8 and the ByteTrack algorithm enables the detection of intrusions into predefined dangerous areas, and that bone conduction wireless earphones are capable of transmitting warning sounds over a distance of approximately 115 meters. However, several challenges remain when considering practical deployment, such as developing methods to set the coordinates of hazardous areas, improving the accuracy of object detection models, and implementing and experimenting with person re-identification algorithms to determine the identity of individuals who have entered hazardous areas.

## VI. Future Research Works

In this study, a system was developed to detect intrusions into hazardous areas and issue warnings to the relevant workers. For practical deployment, a method was also implemented for setting the coordinates of dangerous areas. However, several challenges remain, including improving object detection accuracy and integrating a person re-identification algorithm to determine the identity of individuals entering hazardous zones. Addressing these issues will be the focus of future work.

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## AUTHORS' PROFILE

Kohei Arai, He received BS, MS and PhD degrees in 1972, 1974 and 1982, respectively. He was with The Institute for Industrial Science and Technology of the University of Tokyo from April 1974 to December 1978 also was with National Space Development Agency of Japan from January, 1979 to March, 1990. During from 1985 to 1987, he was with Canada Centre for Remote Sensing as a Post Doctoral Fellow of National Science and Engineering Research Council of Canada. He moved to Saga University as a Professor in Department of Information Science on April 1990. He was a councilor for the Aeronautics and Space related to the Technology Committee of the Ministry of Science and Technology during from 1998 to 2000. He was a councilor of Saga University for 2002 and 2003. He also was an executive councilor for the Remote Sensing Society of Japan for 2003 to 2005. He is a Science Council of Japan Special Member since 2012. He is an Adjunct Professor of University of Arizona, USA since 1998. He also is Vice Chairman of the Science Commission "A" of ICSU/COSPAR since 2008 then he is now award committee member of ICSU/COSPAR. He wrote 77 books and published 670 journal papers as well as 500 conference papers. He received 66 of awards including ICSU/COSPAR Vikram Sarabhai Medal in 2016, and Science award of Ministry of Mister of Education of Japan in 2015. He is now Editor-in-Chief of IJACSA and IJISA. http://teagis.ip.is.saga-u.ac.jp/index.html

Yuya Ifuku, He received BE degree in 2024. He is currently working on research that uses image processing and image recognition in Master's Program at Kurume Institute of Technology.

Mariko Oda, She graduated from the Faculty of Engineering, Saga University in 1992, and completed her master's and doctoral studies at the Graduate School of Engineering, Saga University in 1994 and 2012, respectively. She received Ph.D(Engineering) from Saga University in 2012. She also received the IPSJ Kyushu Section Newcomer Incentive Award. In 1994, she became an assistant professor at the department of engineering in Kurume Institute of Technology; in 2001, a lecturer; from 2012 to 2014, an associate professor at the same institute; from 2014, an associate professor at Hagoromo university of International studies; from 2017 to 2020, a professor at the Department of Media studies, Hagoromo university of International studies. In 2020, she was appointed Deputy Director and Professor of the Applied of AI Research Institute at Kurume Institute of Technology. She has been in this position up to the present. She is currently working on applied AI research in the fields of education.

# Flexible Software Architecture for Genetic Data Processing in Alpaca Breeding Programs

Alfredo Gama-Zapata, Fernando Barra-Quipse, Elizabeth Vidal
Escuela Profesional De Ingeniería De Sistemas, Universidad Nacional De San Agustín De Arequipa, Arequipa, Perú

***Abstract*—Improving alpaca fiber quality is an important objective in the textile industry. There are different kinds of techniques aimed to enhance breeding outcomes. This study proposes and validates a flexible software architecture for managing genetic information in alpaca breeding, integrating genomic selection methods. The proposed architecture consists of three components: 1) Input—capturing data from individual records, pedigree, phenotypic traits, fiber characteristics, genomic, and non-genomic information; 2) Processing—implementing statistical methods such as BLUP, GBLUP, and SSGBLUP, alongside inbreeding coefficient calculation and machine learning techniques; and 3) Output—generating reports for mating list proposals, estimated breeding values, and genetic evaluations. Designing a software architecture for genetic improvement in alpaca breeding programs could help software developers with maintainability, extensibility, and adaptability, considering different kinds of data sources for future advancements in alpaca breeding. This work shows the implementation and validation of software for an alpaca breeding program based on the proposed architecture.**

***Keywords*—Architecture; genomic selection; adaptability**

## I. Introduction

The purpose of alpaca breeding is to improve the textile properties of the fiber [1]. The textile industry seeks quality fibers measured by the fineness and the low variability of its diameter [2]. Recently, new ways to enhance textile production have emerged through genomic selection.

Genetic improvement in alpaca breeding is of great interest, as it aims to optimize productive traits such as fiber quality. Genomic selection refers to using genome-wide and dense markers for predicting breeding values (BV) and the subsequent selection of individuals [3], [4]. To achieve this objective, genetic improvement programs have incorporated advanced data analysis and genetic modeling technologies, driving the development of specialized computational tools.

In this context, software architecture plays a crucial role in building efficient systems for collecting, processing, and analyzing information that enables the genetic improvement of alpacas. Genetic models used in genomic selection for animal breeding require the integration of multiple data sources (pedigree, genotypes, phenotypes, environmental data, etc.), intensive statistical computations, and the delivery of reliable and reproducible results.

In software architecture, different approaches are used to manage large volumes of genetic information efficiently [5]. However, the application of architecture models in alpaca genetic improvement still presents an opportunity for the development of more specialized solutions tailored to this species' specific characteristics. While there have been advancements in software development for managing genetic improvement information in animals [6], [7] there is a lack of software architectures designed explicitly for alpaca genetic improvement, considering the species' unique characteristics and the interoperability between different data sources (genotypic, phenotypic, and environmental).

A flexible architecture would allow a prediction module to be replaced with a more advanced one, without redesigning the entire system. The main objective of this study is to propose and validate a flexible software architecture for managing alpaca genetic information, integrating genomic selection methods and data processing for software developers in this field.

## II. Background

### A. Software Architecture

Software architecture is the structure that comprises software components, their externally visible properties, and the relationships between them. According to Garlan [8], identifying and documenting a software architecture allows other developers to adopt previous architectural structures as a starting point. A well-designed architecture ensures that a system meets key requirements such as maintainability, extensibility, and adaptability [9], these are key attributes that significantly influence the long-term success and usability of software systems [10].

Maintainability refers to the ease with which a software system can be modified to correct faults, improve performance, or adapt to a changed environment. A key factor influencing maintainability is modularity. Modularity refers to a well-structured architecture that allows components to be updated or replaced independently without affecting the entire system.

Extensibility is the capability of a software system to accommodate future growth by adding new features or components without significant rework. Adaptability is the ability of a software system to evolve in response to changing requirements or environments. This characteristic is crucial in today’s fast-paced technological landscape.

### B. Genomic Selection

Genomic selection increases the rate of genetic improvement and reduces the cost of progeny testing by allowing breeders to preselect animals that inherited chromosome segments of greater merit [11]. A Single

Nucleotide Polymorphism (SNP) is a slight difference in the DNA sequence that varies between individuals. These differences act like genetic "markers", helping researchers to track which genes an animal has inherited. Without SNP markers, researchers only rely on pedigree-based selection, which assumes all siblings inherit the same genetics [12]. Computer algorithms and programs are needed to incorporate genomic data into genetic evaluations and to process the rapidly expanding numbers of SNP genotypes.

There are statistical methods widely used in genomic selection to predict genetic merit in livestock breeding: Best Linear Unbiased Predictor (BLUP) [13], Genomic Best Linear Unbiased Predictor (GBLUP) [12] and Single-Step Genomic Best Linear Unbiased Predictor (SSGBLUP) [14].

## III. Methodology

### A. Software Architecture

This study presents software architecture for flexible software development aimed at the genetic improvement of alpacas, emphasizing textile quality. The proposed architecture consists of three components (Fig. 1). Component A -Input: This component captures the necessary data for processing: Individual, Pedigree, Phenotypic, Fiber, Genomic, and Non- Genomic Information. Component B - Processing: Comprises five modules, three of which are statistical methods used in genomic selection: BLUP, GBLUP, and SSGBLUP; the fourth module calculates the INBREEDING COEFFICIENT, and the fifth module allows to include machine learning techniques in order to improve statistical methods performance. Component C - Output: Presents three kinds of reports: Mating List Proposal, Estimated Breeding Values, and Genetic Report.

### B. Component A – Input

Component A considers six different types of input data, described below:

Individual: It considers the animal's ear tag, date of birth, species, breed, color, and sex.

Pedigree: It refers to an alpaca's recorded ancestry including information about its parents, grandparents, and other ancestors.

Phenotypic: In alpaca breeding, key measurable traits include [15]:

- Density: The amount of fiber per unit area on the animal's body. A denser fleece is typically associated with higher fiber yield and superior quality.
- Leg Coverage: The alignment and proportion of the front and hind legs assess whether the animal has a proper and functional stance.
- Head: The overall shape and appearance of the head, including ear positioning, facial profile, and bone structure. It is important for functional and health-related assessments.
- Balance: The overall symmetry and proportion of the alpaca's body, including the relationship between the trunk, legs, and neck. Well-balanced animals are healthier, more productive, and have higher market value.
- Crimp: The shape and uniformity of the curls in the fiber. This parameter is related to the elasticity and softness of the produced textiles. Well-defined, uniform curls are indicators of high-quality fiber.

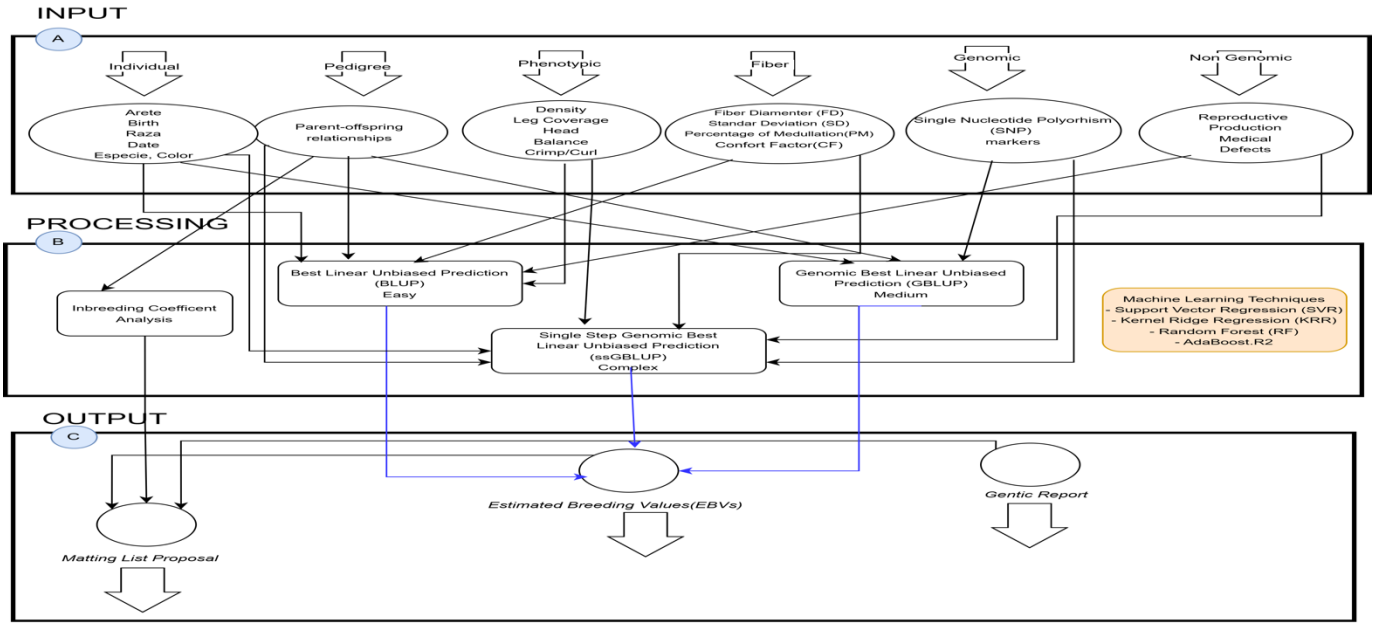


Fig. 1. Generic flexible software architecture for alpaca genetic data processing considering BLUP, GBLUP and SSGBLUP methods.

Fiber: These traits are recorded through direct measurements, such as fiber analysis after shearing. In alpaca breeding, key measurable traits include [16]:

- Fiber Diameter (FD): The thickness of the fiber in micrometers (µm).
- Standard Deviation of Fiber Diameter (SD): A measure of variability in fiber thickness. A lower SD reflects a more uniform fiber, essential for industrial processing.
- Percentage of Medullation (PM): This refers to the proportion of fibers with a hollow or partially hollow core, which affects fiber quality. Lower medullation percentages are preferred for fine textile applications.
- Micron (MIC): Represents fiber fineness, measured in microns (µm). A lower micron count indicates finer fiber, which is preferred in premium markets.
- Comfort Factor (CF): The percentage of fibers in the sample with a diameter of 30 µm or less, determining how "comfortable" the fiber feels against human skin. A higher CF indicates a lower likelihood of irritation.
- Coefficient of Variation (CV): The ratio of SD to the average fiber diameter, expressed as a percentage. It reflects the relative consistency of fiber diameter, with lower CV values being preferred.
- Average Medullated Fiber Diameter (MFD): Provides additional insights into fiber quality, as coarse and medullated fibers can reduce commercial value.

Genomic: This data refers to an organism's DNA information. In animal breeding, this data is used to find genes that influence important traits like fiber quality in alpacas. A Single Nucleotide Polymorphism (SNP) is a slight difference in the DNA sequence that varies between individuals. These differences act like genetic "markers," helping us track which genes an animal has inherited.

Non-genomic: This data refers to a) reproductive: breeding, diagnostics, and births; b) production: type of fleece, weight, staple length; c) medical Information: treatments, diseases, and defects.

### *C. Component B - Processing*

In genetic data processing for alpacas, it is important to have different methodological options such as BLUP, GBLUP, and SSGBLUP because each method offers distinct advantages depending on data availability and quality. BLUP relies on pedigree and phenotypic data, making it suitable when genomic information is limited or unavailable. GBLUP incorporates dense genomic markers to increase accuracy in the estimation of breeding values, which is particularly valuable when aiming for early selection and genetic gain. SSGBLUP integrates pedigree, phenotype, and genomic data into a single framework, allowing for a more comprehensive evaluation that maximizes the use of all available information. These methodological options allow breeders and researchers to tailor the approach based on their specific breeding goals, data structure, and computational resources, ensuring more precise and efficient genetic evaluations for the sustainable improvement of alpaca populations.

This component is the core of the proposed architecture, consisting of five modules that can be executed independently.

Three of them, BLUP (Best Linear Unbiased Prediction), GBLUP (Genomic Best Linear Unbiased Prediction), and SSGBLUP (Single-Step Genomic Best Linear Unbiased Prediction), are statistical methods used in animal breeding and genetic selection. These methods help estimate breeding values to improve desirable traits such as fiber quality in alpacas.

BLUP is a statistical method for estimating breeding values based on pedigree and phenotypic data. It assumes that genetic effects have a normal distribution and estimates genetic merit while adjusting for environmental effects. BLUP uses the relationship matrix called matrix A based on pedigree information. It assumes that the genetic values follow a linear mixed model. Also, it provides unbiased, minimum variance estimates of breeding values [13].

GBLUP is an extension of BLUP that incorporates genomic information using molecular markers (e.g., SNPs). Instead of the pedigree-based relationship matrix A, it uses a genomic relationship matrix G, built from SNP genotypes. GBLUP is more accurate than BLUP, as it captures actual genetic relationships rather than assuming them from pedigrees [12].

SSGBLUP is an improved version of GBLUP that combines pedigree, phenotype, and genomic data in a single step. It integrates both the traditional relationship matrix A and the genomic relationship matrix G into a combined relationship called matrix H. SSGBLUP allows for simultaneous evaluation of genotyped and non-genotyped animals [14].

Having this three statistical model options is important because developers and stakeholders could face different scenarios. The BLUP method is the best choice if only pedigree and phenotype data (fiber records) are available. If a genomic dataset is available, GBLUP is the method to use. Finally, if a mix of genotyped and non-genotyped alpacas exists, SSGBLUP is the option to select.

Using Machine Learning Techniques (MLT) in the genomic prediction of animal reproductive traits allows for improved prediction accuracy [17], [18], [19]. In genomic prediction, machine learning regression methods such as Support Vector Regression (SVR) [20], Kernel Ridge Regression (KRR) [21], Random Forest (RF) [22], and AdaBoost.R2 [23] are increasingly used to model the complex, nonlinear relationships between high-dimensional genetic marker data and quantitative phenotypic traits. These methods are particularly valuable in animal breeding, where accurate prediction of breeding values based on genomic information enables more efficient selection of superior individuals, thereby accelerating genetic gain.

SVR utilizes kernel functions to model complex, nonlinear associations between genetic markers and traits of interest. In the context of genomic selection, SVR handles high-dimensional SNP datasets by projecting them into a higher-dimensional feature space where linear relationships can be identified. SVR allows to capture subtle genetic effects that contribute to phenotypic variation.

KRR combines kernel methods' flexibility with ridge regression's regularization strength. In animal breeding, KRR helps model additive and non-additive genetic effects using non-linear kernels (e.g., Gaussian, polynomial) to map marker data into a higher-dimensional space. KRR enhances the analysis of traits influenced by many small-effect loci, allowing accurate estimation of genomic breeding values.

RF is an ensemble learning method based on decision trees for capturing interactions and nonlinear effects between genetic markers. RF's robustness to noise and ability to handle significant input variables without feature selection makes it a good option for animal breeding datasets, which often involve thousands of SNPs and limited sample sizes.

AdaBoost.R2 is particularly effective in emphasizing difficult-to-predict individuals, thereby refining predictions of phenotypic traits with heterogeneous genetic architectures. By adjusting sample weights based on previous errors, the algorithm focuses learning efforts on underrepresented or outlier phenotypes, improving the prediction of genomic breeding values and enhancing selection accuracy for traits with skewed or non-normal distributions.

Finally, the module Inbreeding Coefficient Analysis identifies common ancestors. This module analyzes the alpaca's pedigree chart to identify any ancestors on the sire's (father's) and dam's (mother's) sides. The most common method is Wright's Equation [24] shown in Eq. (1). The coefficient of consanguinity F, also known as the inbreeding coefficient, measures the probability that an individual has inherited two alleles at a given locus from a common ancestor. It is crucial in alpaca breeding to avoid excessive inbreeding, which can lead to genetic defects and reduced vigor.

$$F_\chi = \sum(\frac{1}{2})^{n_1+n_2+1}(1+F_A) \quad (1)$$

where,

$F_\chi$ = Inbreeding coefficient of the individual (X).

$n_1$ =Number of generations between the common ancestor and the sire.

$n_2$ = Number of generations between the common ancestor and the dam.

$F_A$ = Inbreeding coefficient of the common ancestor (if unknown, assume 0).

$\sum$ = Summation over all common ancestors.

### D. Component C – Output

This component presents tree kind of outputs.

The Estimated Breeding Value (EBV) is a numerical prediction of an alpaca's genetic potential for a specific trait. EBVs help breeders select animals that pass desirable genetic traits to their offspring, improving overall herd quality.

The Genetic Report provides three items: a) pedigree analysis: ancestry verification, inbreeding coefficient; b) performance data: Measured traits such as fleece, growth, and reproduction; c) Genomic information: SNP markers, parentage confirmation.

The Mating List Proposal is a structured plan that suggests the optimal pairings of male and female alpacas to achieve specific breeding objectives. It maximizes genetic progress, improves desirable traits, and minimizes inbreeding while ensuring herd sustainability.

## IV. Results and Discussion

### A. Implementation

The software developed is part of the Pacomarca Project [25] a research and genetic improvement program for alpacas in Peru. Its main objective is to manage and analyze genetic and phenotypic data to improve the quality of alpaca fiber, optimize selection programs, and maximize reproductive efficiency. The software focuses on pedigree and genealogical data registration, phenotypic data analysis, genotyping, and genetic evaluation, as well as simulation and prediction of genetic improvement.

Fig. 2 shows the architecture for the developed software. The Input component considers only five type of input data: the alpaca's individual, pedigree, phenotypic, fiber, and non- genomic information (Fig. 3).

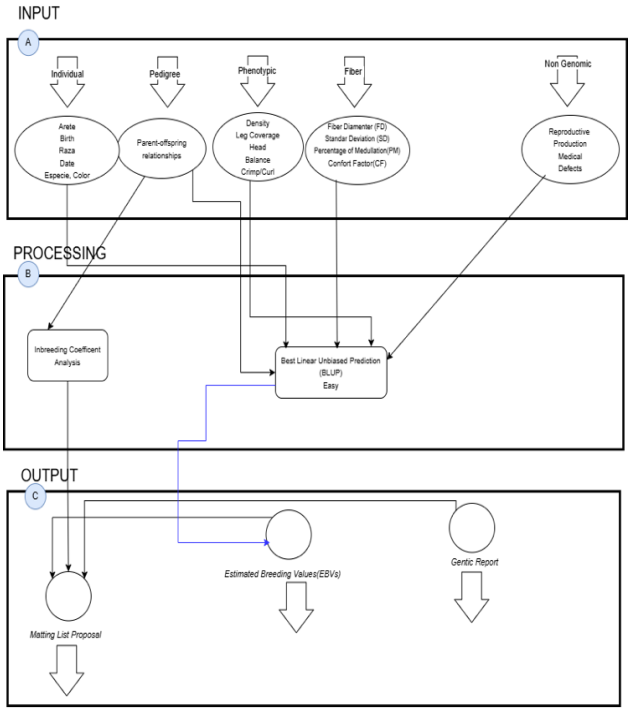


Fig. 2. Software architecture for alpaca breeding – Pacomarca project. It implements BLUP method and inbreeding coefficient analysis.

Processing component implements the BLUP module for genetic processing and the Inbreeding Analysis module. We show an implementation in Python. Fig. 4 shows the loading of pedigree, phenotype, and SNP data. Fig. 5 shows the processing of the matrices. Fig. 6 shows the processing of the BLUP method in line 19. Although the Pacomarca project has implemented the BLUP method only, the code for implementing GBLUP and SSGBLUP is also presented in lines 22 and 25, respectively. Fig. 7 shows the code for the Inbreeding Coefficient Analysis. Finally, Fig. 8 shows the result of the Estimated Breeding Value.

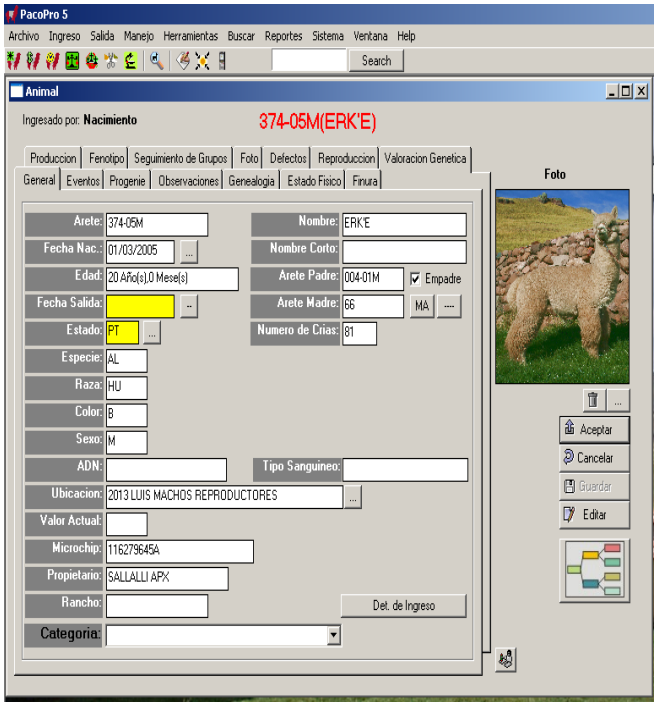


Fig. 3. Input component: software's main interface - individual, pedigree, phenotypic, fiber, and non-genomic information.

```python
import numpy as np
import pandas as pd

# Simulated Pedigree Data (Parent-Offspring Relationships)
pedigree_data = pd.DataFrame({
    "ID": range(1, 11),
    "Father": [0, 0, 1, 1, 2, 2, 3, 3, 4, 4],
    "Mother": [0, 0, 5, 5, 6, 6, 7, 7, 8, 8]
})

# Simulated Phenotypic Data (Fiber Diameter)
phenotype_data = pd.DataFrame({
    "ID": range(1, 11),
    "Fiber_Diameter": [21.5, 22.3, 21.8, 23.1, 22.0, 21.7, 22.5, 23.8, 21.9, 22.1]
})

# Simulated SNP Genotype Matrix (0, 1, 2 encoding)
np.random.seed(123)
snp_data = pd.DataFrame(
    np.random.choice([0, 1, 2], size=(10, 5)),
    columns=[f"SNP_{i+1}" for i in range(5)]
)
snp_data.insert(0, "ID", range(1, 11))  # Add ID column
```

Fig. 4. Processing component: Loading data.

## B. Validation

The software was validated with four experts from the alpaca breeding community in Peru and Spain. The instrument used was the User Experience Questionnaire (UEQ), which measures six dimensions: a) Attractiveness refers to the overall impression of the software. b) Perspicuity refers to whether the system is easy to get familiar with and use. c) Efficiency refers to whether users can complete tasks without effort. d) Dependability: assesses whether the user controls the interaction. e) Stimulation: evaluates whether the software is exciting and motivating. f) Novelty: considers whether the software design is creative and captures users' interest [26].

The scale ranges from -3 (terribly bad) to +3 (extremely good), with values between -0.8 and 0.8 representing a more or less neutral evaluation. Values above 0.8 indicate a positive assessment, while values below -0.8 indicate a negative evaluation. Table I presents the values of the six dimensions.

```python
from scipy.spatial.distance import pdist, squareform

# Compute Pedigree-Based Relationship Matrix (A-matrix)
def compute_a_matrix(pedigree):
    n = len(pedigree)
    A = np.eye(n) * 1.0  # Identity matrix as base
    id_index = {id: idx for idx, id in enumerate(pedigree["ID"])}

    for i, row in pedigree.iterrows():
        father, mother = row["Father"], row["Mother"]
        if father in id_index:
            A[i, id_index[father]] = 0.5
            A[id_index[father], i] = 0.5
        if mother in id_index:
            A[i, id_index[mother]] = 0.5
            A[id_index[mother], i] = 0.5

    return A

A_matrix = compute_a_matrix(pedigree_data)

# Compute Genomic Relationship Matrix (G-matrix)
def compute_g_matrix(snp):
    snp_values = snp.iloc[:, 1:].values
    n_markers = snp_values.shape[1]
    G = np.corrcoef(snp_values)  # Simple correlation-based similarity
    return G

G_matrix = compute_g_matrix(snp_data)

# Compute Single-Step Relationship Matrix (H-matrix)
H_matrix = 0.95 * G_matrix + 0.05 * A_matrix
```

Fig. 5. Processing component: compute relationships matrix.

```python
import statsmodels.api as sm

# Function to solve Mixed Model Equations
def solve_mixed_model(y, K):
    n = len(y)
    X = np.ones((n, 1))  # Intercept
    K_inv = np.linalg.pinv(K)  # Inverse of relationship matrix

    # Mixed Model Equation: y = Xb + Zu + e
    lhs = X.T @ K_inv @ X  # Left-hand side (X'K^-1X)
    rhs = X.T @ K_inv @ y  # Right-hand side (X'K^-1y)

    beta_hat = np.linalg.solve(lhs, rhs)  # Fixed effect estimate
    u_hat = K_inv @ (y - X @ beta_hat)  # Breeding values

    return beta_hat, u_hat

#Apply BLUP (Pedigree Only)
blup_beta, blup_ebv = solve_mixed_model(phenotype_data["Fiber_Diameter"].values, A_matrix)

# Apply GBLUP (Genomic Only)
# gblup_beta, gblup_ebv = solve_mixed_model(phenotype_data["Fiber_Diameter"].values, G_matrix)

# Apply ssGBLUP (Single-Step)
# ssgblup_beta, ssgblup_ebv = solve_mixed_model(phenotype_data["Fiber_Diameter"].values, H_matrix)
```

Fig. 6. Processing component: Solving BLUP/ GBLUP/ SSGBLUP.

```python
def calculate_inbreeding(common_ancestors):
    """
    Calculate the inbreeding coefficient using Wright's formula.
    :param common_ancestors: List of tuples where each tuple contains (n1, n2, F_A)
                             n1 = Generations from common ancestor to sire
                             n2 = Generations from common ancestor to dam
                             F_A = Inbreeding coefficient of the common ancestor
    :return: Inbreeding coefficient (Fx)
    """
    F_x = 0

    for n1, n2, F_A in common_ancestors:
        F_x += (1 / 2) ** (n1 + n2 + 1) * (1 + F_A)

    return round(F_x, 6)  # Round to six decimal places for precision

# Example usage
common_ancestors = [
    (3, 2, 0.05),  # Common ancestor A: 3 generations from sire, 2 from dam, FA = 0.05
    (4, 3, 0.02)   # Common ancestor B: 4 generations from sire, 3 from dam, FA = 0.02
]

Fx = calculate_inbreeding(common_ancestors)
print(f"Inbreeding Coefficient (Fx): {Fx}")
```

Fig. 7. Processing component: Inbreeding coefficient analysis.

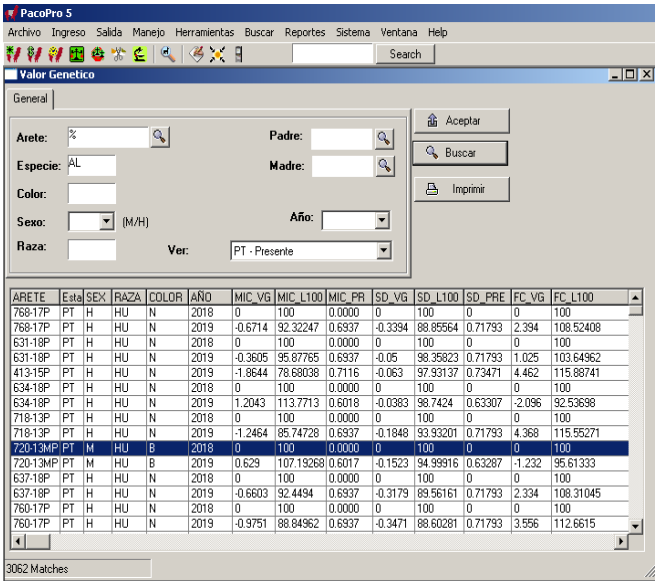


Fig. 8. Result component: Estimated breeding value.

TABLE I. USER EXPERIENCE RESULTS

| Dimension | Mean | SD |
|---|---|---|
| Attractiveness | 1.750 | 1.27 |
| Perspicuity | 1.125 | 2.06 |
| Efficiency | 2.063 | 0.89 |
| Dependability | 1.125 | 1.23 |
| Stimulation | 1.750 | 1.42 |
| Novelty | 1.375 | 0.60 |

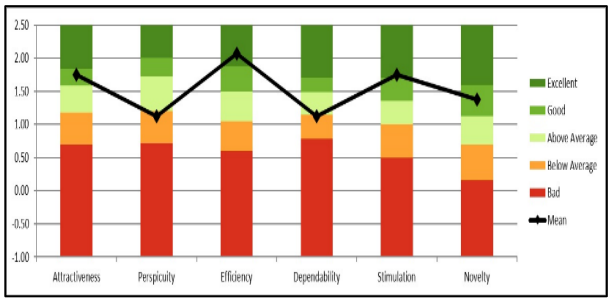


Fig. 9. Result of user experience questionnaire qualitative scale.

Fig. 9 shows a qualitative scale. The highest value is Efficiency, with an average score of 2.063, considered excellent. The second highest value was Stimulation, with an average score of 1.750, also considered excellent. Attractiveness obtained an average score of 1.750, rated as "good." The result reflects that users found the system visually appealing and pleasant to use. The score suggests that the system's design and aesthetics were positively received. Novelty obtained an average score of 1.375, rated as "good."

This result indicates that users perceived the system as innovative and featuring characteristics that captured their interest. Dependability obtained an average score of 1.125, below the average. This result may indicate that users did not feel complete control over the system, possibly due to a lack of clarity in the available options or intuitive handling. Finally, transparency obtained an average score of 1.125, which was also below the average. This result may reflect that users did not clearly understand how the system works or processes information.

### C. Discussion

The main objective of this study was to propose and validate a flexible software architecture for managing alpaca genetic information, integrating genomic selection methods and data processing. A three-layer architecture has been created, where the Processing component consists of three genetic analysis modules and one module for analyzing the inbreeding coefficient. The architecture has been validated by implementing software that employs the BLUP method for genomic selection.

A specialized architecture for this type of system allows for flexibility when implementing solutions based on the available data, regarding using BLUP, GBLUP, or SSGBLUP methods. This type of architecture would allow for improved performance and adaptation to changing environments. Modularity would enable components to be updated or replaced independently without affecting the entire system. For example, while the processing methods were implemented in Python, depending on the developers' expertise, they could be implemented in ASReml-R [27]. ASReml-R is widely used in animal breeding and quantitative genetics because it efficiently handles large datasets.

Regarding extensibility, the proposed architecture allows the software system to accommodate future growth by adding new features or components without significant rework. For instance, this architecture could incorporate new genomic selection processing modules, such as BayesA or BayesB [28].

Additionally, this architecture could evolve in response to changing requirements or environments, a crucial characteristic in today's fast-paced technological landscape. For example, within the Processing component, it would be possible to introduce a new module integrating Machine Learning techniques to enhance the results obtained with BLUP, GBLUP, or SSGBLUP. Recent literature has already demonstrated progress in this area; Gianola et al. [29] presented enhancing genome-enabled prediction by bagging genomic BLUP. Wang et al. [18] implemented machine learning to improve the accuracy of genomic prediction of reproduction traits in pigs. Gianola et al. [30] presented Machine learning and genetic improvement of animals and plants: where are we? Santana et al. [31] presented a Genome-enabled cattle stability classification under a machine-learning framework.

The UEQ results showed that Efficiency had the highest score. Given the nature of the developed system, this result reinforces the idea that users obtained the expected outcomes.

This proposal highlights the importance of software architectures, especially in specific domains such as genetic improvement in alpaca breeding. This architectural model could serve as a foundation for use in other livestock species.

This work has some limitations; the main one is that only one implementation example was carried out, explicitly using the BLUP method. In future work, tests will be conducted using

GBLUP or SSGBLUP methods. A second limitation is the number of experts who tested the system. User access was relatively limited because this is a highly specialized field. Another limitation lies in the user experience evaluation, as the sample consisted of four experts in alpaca genetic improvement. This is due to the highly specialized nature of the area, which limits the ability to generalize the results obtained. In future work, it is intended to expand the usability evaluation of the proposed architecture with more experts in alpaca breeding from different regions.

## V. Conclusion

This study addresses the design of flexible software architectures for genetic data processing in alpaca breeding programs. The proposal shows that it is possible to integrate specific input data, advanced algorithms, and predictive models based on BLUP, GBLUP, and SSGBLUP to optimize selection and breeding processes.

This work contributes to the field by providing a practical reference framework for designing and evaluating software architectures specialized in genomic analysis. It integrates computational methodologies that reduce processing time and improve the accuracy of predictive models. Additionally, it highlights the importance of using machine learning to efficiently manage large volumes of genomic information.

As an important conclusion, the study emphasizes that the evolution of software architectures for genomic selection should be guided by solid engineering principles aligned with the scientific community's and livestock producers' needs. For future work, it is suggested to explore the integration of artificial intelligence to enhance predictive model accuracy and develop automated systems that facilitate decision-making in alpaca breeding programs.

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# Method for Providing Exercise Instruction that Allows Immediate Feedback to Trainees

Kohei Arai[1], Kosuke Eto[2], Mariko Oda[3]
Department of Information Science, Saga University, Saga City, Japan[1]
Graduate School, Kurume Institute of Technology, Kurume City, Japan[2]
Applied AI Laboratory, Kurume Institute of Technology, Kurume City, Japan[3]

***Abstract*—Method for providing exercise instruction that allows immediate feedback to trainees is proposed. The purpose of this research is to combine artificial intelligence technology and motion analysis methods to build an effective vocational training support program aimed at supporting the employment of children with disabilities. Specifically, we develop a system that uses DTW (Dynamic Time Warping) to calculate the similarity between the trainee's motion and the model motion, and scores the results based on the results. This system will enable optimal instruction for each disabled child, and is expected to improve motion skills and promote learning motivation. Furthermore, by providing scored feedback, we aim to improve the traditional evaluation that relies on the subjectivity of the instructor and provide an intuitive and easy-to-understand means of confirming results for trainees. In this research, we use skeletal detection technology to record the trainee's three-dimensional coordinate data and perform quantitative evaluation. In addition, we will design a program that allows trainees to visually check their own progress through a motion evaluation function and maximize the learning effect. Through experiment, it is found that the proposed method does work for motion trainings at supporting the employment of children with disabilities. Also, it is found that immediate feedback is better than conventional delayed feedback.**

***Keywords*—Motion training; immediate feedback; DTW (Dynamic Time Warping); children with disabilities; skeletal detection**

## I. Introduction

Employment support for children with disabilities plays an important role in their mental and social development. Children with disabilities require individualized instruction because their physical characteristics and growth stages are different [1]. For example, children with Autism Spectrum Disorder (ASD) often have sensory processing difficulties and delayed motor functions, and it is said that it is necessary to promote sociality and emotional stability through exercise therapy and work-study classes. Furthermore, in Japan, employment support and social independence support for children with disabilities are emphasized.

In support schools and special support classes, employment support is incorporated into the learning program, but traditional instruction relies mainly on the teacher's experience and intuition. Such teaching methods are not optimized for individual children, and the subjective nature of effectiveness measurement is a challenge.

On the technical side, the development of analytical methods such as skeletal detection technology and Dynamic Time Warping (DTW) has expanded the possibilities for objective evaluation in various fields [2]. By utilizing these technologies, it is expected that effective instruction and feedback can be provided to each child with a disability, solving the problems in the field of support.

The purpose of this research is to combine artificial intelligence technology and motion analysis methods to build an effective vocational training support program aimed at supporting the employment of children with disabilities. Specifically, we develop a system that uses DTW to calculate the similarity between the learner's motion and the model motion and scores the results.

This system will enable optimal instruction for each disabled child and is expected to improve their motor skills and promote their motivation to learn. Furthermore, by providing scored feedback, we aim to improve the traditional evaluation that relies on the subjectivity of the instructor and provide learners with an intuitive and easy-to-understand means of confirming results.

In this research, we use skeletal detection technology to record the learner's three-dimensional coordinate data and perform quantitative evaluation. In addition, we will design a program that allows learners to visually check their own progress through a motion evaluation function and maximize the learning effect.

The key thing is immediate feedback to trainees. Delayed feedback is not effective in comparison to the immediate feedback. To provide feedback on a real time basis, motion prediction is necessary. Although there are so many prediction methods, Recursive Least Squares (RLS) method is the most accurate and efficient one [3]. Therefore, the proposed method and system utilizes the DTW with RLS prediction method in comparison between model motion and trainees' motion.

In the next section, related research works are to be reviewed followed by the proposed method. Then, experiments with a small number of samples are described. After that, conclusion is described together with some discussions.

## II. Related Research Works

Many of the research proposals to date have used skeletal detection technology to analyze motion and assist programs. For example, in a study of physical therapy using Microsoft's Kinect sensor, a system has been developed that records the motions of

people with disabilities and evaluates their motor skills. In addition, a motion analysis system specialized for children with disabilities has attempted to objectively monitor growth by quantifying the children's motor skills.

"Recognition and Scoring Physical Exercises via Temporal and Relative Analysis of Skeleton Nodes Extracted from the Kinect Sensor" [4].

This paper describes a method for recognizing and scoring motions using skeletal joint data from the Kinect sensor. By extracting features from the joints and generating relative descriptors to quantify the relationships during motion, high accuracy in labeling and scoring is achieved.

On the other hand, research is also underway on motion similarity evaluation using DTW. DTW is a method for efficiently calculating the similarity between time series data and has a track record of application in speech recognition and the medical field in addition to physical therapy. For example, it has been used to perform accurate movement analysis in patient rehabilitation, and efforts have been reported to quantify the results of motor learning.

While these studies have confirmed the effectiveness of technology, not enough research has been done on its adaptability to children with disabilities or on methods of providing real-time feedback of movement evaluation results to children and students. A scoring system that allows children and students to intuitively understand their progress in acquiring movements could contribute to improving their motivation to learn, but there are few concrete examples of its implementation.

The following publications contain important research findings on the methods, effects, and application of immediate feedback during training.

Continuous concurrent feedback degrades skill learning is discussed with implications for training and simulation [5]. Meanwhile, augmented visual, auditory, haptic, and multimodal feedback in motor learning are reviewed [6]. Harnessing and understanding feedback technology in applied settings is discussed [7].

Evidence for biomechanics and motor learning research improving golf performance is introduced [8]. On the other hand, information feedback for motor skill learning is reviewed [9]. The roles and uses of augmented feedback in motor skill acquisition are discussed [10].

The effects of augmented auditory feedback on psychomotor skill learning in precision shooting are clarified [11]. Meanwhile, understanding the role of augmented feedback (The good, the bad, and the ugly) is discussed [12].

The paper examines the effects of immediate feedback in athletic instruction and effective methods of immediate feedback. The authors clarified that immediate feedback during exercise is effective in improving athletic technique and performance, and cited clarity, immediacy, simplicity, and positive expressions as effective methods of immediate feedback [13].

The systematic review summarizes past research on the effects of immediate feedback in athletic instruction. The authors show that immediate feedback is effective in improving athletic skills and performance, and point out that the content, timing, and method of feedback are important factors that affect its effectiveness [14].

The meta-analysis integrates and analyzes past research on the effects of immediate feedback in athletic instruction. The authors show that immediate feedback is moderately effective in improving athletic skills and performance, and point out that the content, timing, and method of feedback are important factors that affect its effectiveness [15].

The study experimentally examined the effect of feedback frequency on the learning effect in motor skill learning and suggests that providing feedback (perceptual information) in near real time is advantageous for acquiring and adjusting a movement [16].

The study systematically reviews the role of feedback in education in general and is also useful for deepening understanding of the significance and effectiveness of immediate feedback in the skill acquisition process, such as in motor instruction [17].

The study reports on the development of a system that uses sensors and real-time processing technology to instantly analyze a trainee's movements and provide feedback, and an evaluation of its usefulness [18].

An example of an evaluation of how a method of providing immediate feedback during motor learning in a Virtual Reality (VR) environment affects learning outcomes and shows an example of a teaching method utilizing the latest technology [19].

This research is an example of the development of a system that uses wearable sensors to instantly analyze and evaluate a trainee's movements and provide feedback. An approach based on real-time motion capture and analysis technology is presented [20].

From the above, current employment support systems often depend on the experience of the instructor, and optimal instruction is not provided for each learner. In addition, because the evaluation results are subjective, it is difficult to quantitatively grasp the progress and improvement points of the learner.

Furthermore, several systems that combine skeletal detection technology and DTW have been proposed, and their effectiveness has been demonstrated, but there is still insufficient development of application examples specific to children with disabilities and systems that provide visual and audio feedback on the results of movement evaluation.

## III. Proposed Method

### A. Research Approach

In this study, we took the following steps to build a program to support vocational training for children with disabilities. These steps comprehensively cover everything from acquiring the subject's movement data to providing feedback and aim to effectively design and implement the entire system.

*1)* Use of skeletal detection technology.

*2)* Recording of model movements.
*3)* Calculation of similarity using DTW.
*4)* Judgment of movement quality.
*5)* Feedback by scoring.
*6)* Support for repeated learning.

### B. Technical Issues

These are the following technical issues: Skeletal Detection and Motion Similarity Measurement as well as Analysis and Motion Prediction.

*1)* Skeleton detection technology is a technology that detects the major joints and parts of the human body in real time and records them as three-dimensional coordinate data. In recent years, this technology has been applied in the following areas.

*a) Rehabilitation:* It is used to monitor the rehabilitation process of patients and evaluate the accuracy of their movements and areas for improvement. Sensors such as Microsoft Kinect and Intel RealSense have realized simple and highly accurate skeletal detection.

*b) Sports analysis:* It is used to analyze athletes' movements and is useful for improving performance and preventing injuries. Methods that maximize training effects by evaluating the efficiency of movements based on skeletal detection data are becoming widespread.

*c) Education and entertainment:* In games and interactive educational content, skeletal detection technology is also useful for building systems that recognize user movements and respond in real time.

In this study, we focused on the ThreeDPose library. ThreeDPose Tracker is an image recognition and pose estimation AI technology developed in-house by Digital Standard Co., Ltd. By using the coordinates output by the TDPT system to manipulate the bone angles of the avatar, the app enables full-body tracking using only a camera, without the need for trackers on the body. This app is widely used by many people, including as a VTuber or for expressing the whole body in the metaverse.

Another candidate is MedeaPipe. Mediapipe is an open-source skeleton detection library provided by Google that can detect human skeletons in real time from camera footage and obtain the 3D coordinates of each joint with high accuracy. Due to its light weight and high accuracy, we decided that it would be the ideal choice for our employment support program for children with disabilities.

*2)* DTW is a method to calculate the similarity between time series data. This method can accurately compare time series data of different lengths by minimizing the distance between data while taking into account the time axis shift.

*a) Speech recognition:* DTW is widely used in speech recognition to compare speech data while correcting for differences in different speakers and speech rates.

*b) Medical field:* DTW is used to compare patients' motion data and identify rehabilitation progress and abnormal movements. Using DTW, it is possible to quantitatively evaluate the effectiveness of rehabilitation.

*c) Physical therapy support:* DTW is considered important as a basic technique for comparing model movements and the learner's movements and providing individualized instruction, especially in physical therapy for disabled children and the elderly.

In this study, we aim to use DTW to evaluate the similarity between the learner's movements and the model movements and quantitatively measure the effectiveness of employment support. This makes it possible to provide feedback based on objective data rather than relying on traditional subjective evaluations.

*3)* Analysis and prediction of motion time series data using the RLS method, a type of machine learning algorithm.

### C. Procedure of the Proposed Method

The steps of the proposed method are as follows.

*1) Analyzing the learner's movements using skeletal estimation:* Extract the learner's three-dimensional coordinate data using skeletal estimation technology.

*2) Creating exercise movements using a 3DCG character:* Create an animation of the exercise movements of a 3DCG character to present a model of physical training exercises.

*3) Calculating the similarity between the ideal movements and the learner's movements:* Determine the ideal movements in work and the learner's skeletal movements and calculate the similarity using Time Warp.

*4) Judging the quality of the learner's physical movements:* Judgment the quality of the learner's work movements from the similarity obtained in (3) and the learner's skeletal coordinate data.

*5) Predicting the learner's movements using RLS:* Predict abnormal movements in advance using the RLS method based on the similarity obtained in (3).

## IV. Experiment

### A. Experimental Set-Up

As examples of physical movement practice to be learned, we chose basic movement’s characteristic of Japanese people, such as bowing, correct posture, and standing upright. We built a system that allows students to check sample movements (Fig. 1(a)) and their own movements (Fig. 1(b)), and to analyze and evaluate the students' physical movements. Furthermore, we set up the system to provide feedback in real time based on the evaluation results.

The learner's skeletal coordinate information is extracted, and the extracted coordinate information is compared with the data of the sample movement to judge the movement. This mode provides real-time feedback to the learner based on the judgment results. Unlike the comparison confirmation mode where you review the data later, feedback is given at each stage during training. By achieving these, the goal is to "develop a system that provides efficient employment support." The procedure is as follows.

*1)* Recognize the learner with a camera

*2)* Extract skeletal coordinated information

*3)* Based on the extracted skeletal coordinate data

(a) Model motion (b) Trainee motion

Fig. 1. Example of pictures for training bowing.

Calculate the similarity between the model movement and the learner's movement.

*4)* Judgment result based on the similarity.

*5)* Real-time feedback, for example, "Please lower your head a little more," "Stretch your back," "Put both hands on your thighs," etc.

As for the skeleton extraction, MediaPipe does work so well. An example is shown in Fig. 2. Green colored lines show the skeleton of the actual trainee on the right side of the picture.

Fig. 2. Example of the extracted skeleton of the trainee.

### B. *Preliminary Experiment for Confirmation of Effect of the Feedback Ways (Real-Time or Post-Exercise)*

Preliminary experiment is conducted for confirmation of effect of the feedback ways (Real-Time or Post-Exercise). We investigated and analyzed the learning effects of real-time feedback and post-exercise feedback on learners. Six university students from Kurume Institute of Technology participated in this study.

Students who participated in the experiment were asked to perform two types of stretching exercises to prevent back pain.

*1)* Watch video A for stretching exercises to prevent back pain.

*2)* Perform exercise A without real-time feedback.

*3)* Receive feedback after exercise A.

*4)* Repeat (1) to (4) until exercise A is mastered.

As for exercise B

*5)* Watch video B for stretching exercises to prevent back pain.

*6)* Perform exercise B while receiving real-time feedback.

*7)* Repeat (1) to (3) until exercise B is mastered.

*8)* Conduct a survey to analyze the difference in the effects of the two types of feedback.

Both exercise A and B are in the YouTube site of https://www.youtube.com/watch?v=koelvnexy3g. Examples of exercise A and B are shown in Fig. 3(a) and (b), respectively.

(a) Exercise Model A (b) Exercise Model B

Fig. 3. Examples of the model exercise A and B.

The results of the feedback survey are as follows. Six students were targeted; feedback after the exercise was performed, and real-time feedback, where feedback is given while the student is performing the exercise. Table I shows the impact that these two methods had on the students.

The results showed that "stretching with real-time feedback" was easier to understand and maintained motivation compared to "stretching with delayed feedback." It was also found that the number of times required to master the movements was fewer with real-time feedback than with post-exercise feedback. Therefore, a real-time feedback system is intended to create.

TABLE I. RESULT FROM THE EXPERIMENT FEEDBACK EFFECTS COMPARISON BETWEEN REAL-TIME AND POST-EXERCISE

| | **Post Feedback** | **Real-Time Feedback** |
|---|---|---|
| Ease of conveying instructions | 0 人 | 6 |
| Maintaining motivation | 0 人 | 6 |
| Average number of times required to learn | 2.7 | 1 |

Mediapipe was started via a camera or video, and the learner's movements were converted into time-series data of the coordinates of each joint after skeleton detection. The similarity between the example and the learner was evaluated using a similarity judgment system based on DTW, and feedback was given if the similarity was low.

Comparisons of time-series data were made using the same method used to measure the distance and similarity between the time-series data of the joint coordinates of the example and the learner. An example of the comparison of two time-series data, Data 1 and 2 is shown in Fig. 4. At this time, the distance between each point of the two-time series was calculated in a brute-force manner as a concept of time warp, and the combination with the smallest distance among all patterns was found to be the similarity.

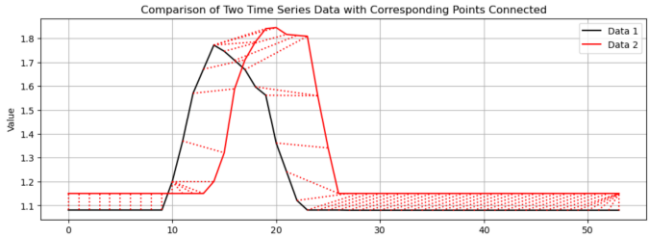
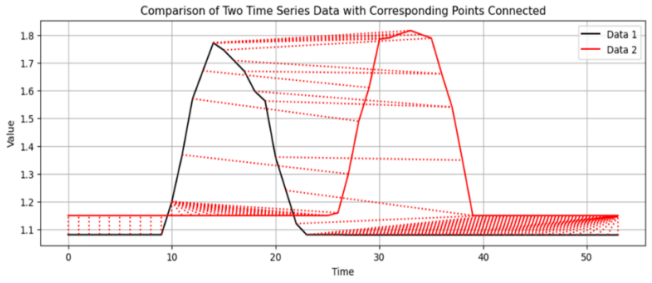


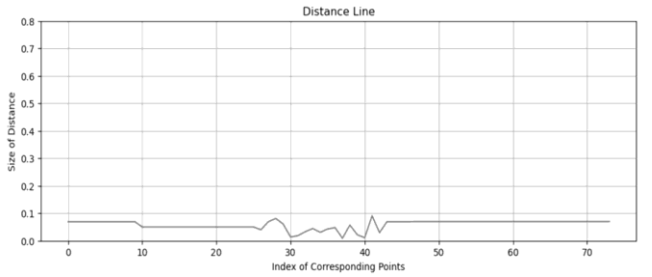

Fig. 4. Example of the comparison of two time-series data, Data 1 (Black) and Data 2 (Red).

We thought that time warping would make it possible to evaluate movements because it can find "similar" movement patterns even if there is a time lag. The graph in Fig. 4 shows the DTW when the correct movement is made. As a result of matching the movements, we can see that the movements are exactly the same.

Also, even if the bow is the same as the previous one, and the timing of the learner's and the model's movements are out of sync (Fig. 5(a)), it can still be matched like this and evaluated as a correct movement. Fig. 5(b) shows a graph of the similarity in this case. The smaller the fluctuation here, the more similar the movements are. Here, the fluctuation is small, and it can be recognized as a bow with the same movement.



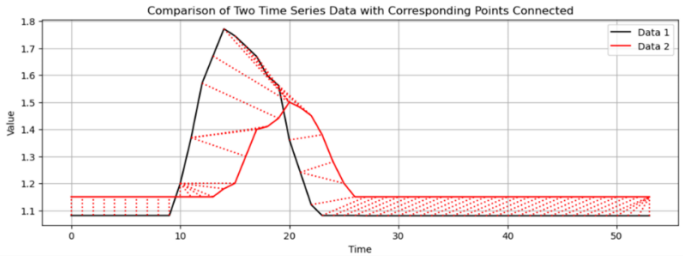

(a) DTW



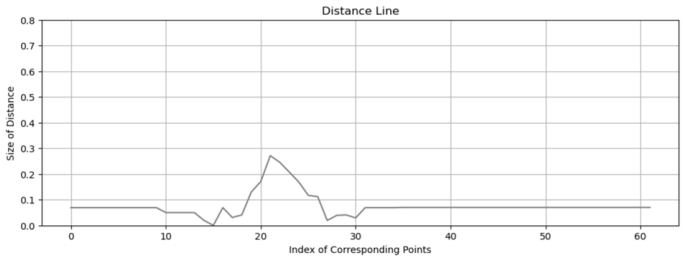

(b) Similarity

Fig. 5. Example of delayed bowing motion.

Also, when the learner is performing the movement itself, but the movement is shallower than the example, the fluctuation range becomes slightly larger, indicating that the movement is insufficient as shown in Fig. 6. When the movement performed by the learner is significantly different, the fluctuation range of the graph below also becomes larger, indicating that the movement is different.




(a) DTW




(b) Similarity

Fig. 6. Example of the case when the bow is shallow.

To make it easier for students to understand the evaluation of their own movements, we have made it possible to score the similarity using DTW. In addition to the similarity, we have incorporated other factors such as the depth of the movement and the time it takes to start the movement into the scoring criteria, allowing for detailed scoring.

The screenshot of the display of the developed system is shown in Fig. 7. In the display, there are scores, the comments (in this case “Well done”), the radio bottom to the trainee (Try Again, Read the Comments and Return).

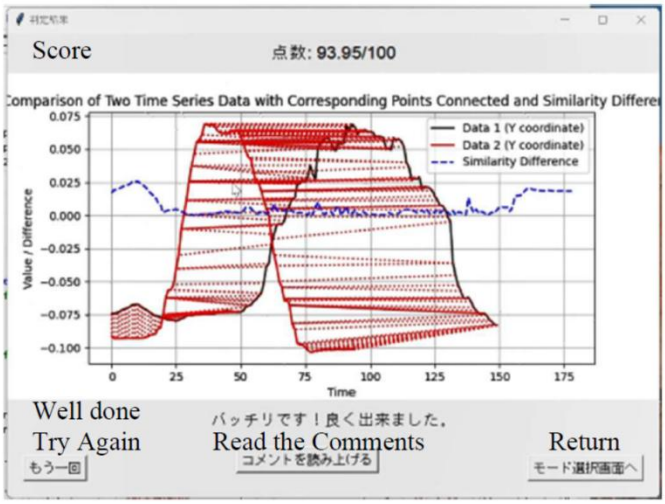
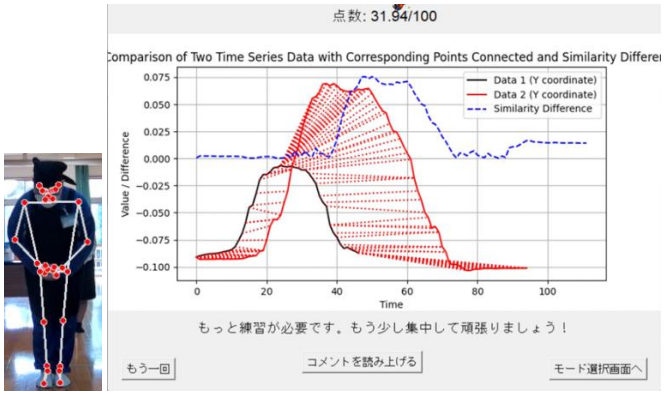
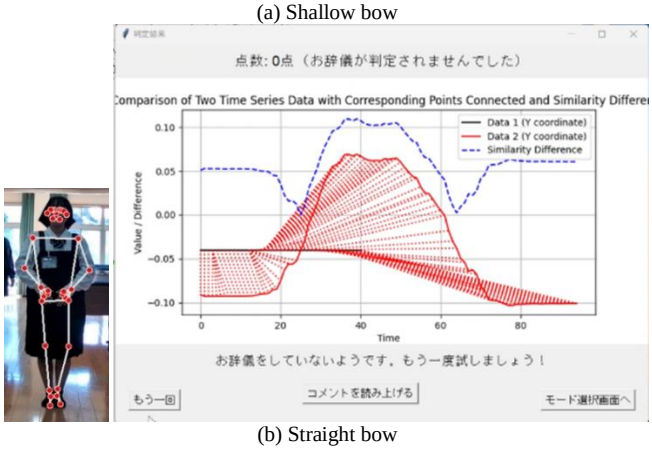



Fig. 7. Screenshot of the display of the developed system.

Two examples, a shallow bow and a straight bow, are shown in Fig. 8(a) and (b), respectively.




(a) Shallow bow




(b) Straight bow

Fig. 8. Examples of a shallow bow and straight bow.

Fig. 9 shows the students using this experimental system to practice physical movements (practicing bowing). As a result, it was found that students can be expected to maintain their motivation by continuing to practice while having fun as if it were a game. In addition, they were seen to try again and again on their own initiative, and all three students who participated in the experiment were able to achieve a score of 90 or more.

Fig. 9. Photo of the students using this experimental system to practice physical movements (practicing bowing).

As mentioned in the experiment, the trainees tried again and again to get a score of 90 or more, suggesting that the program is effective in maintaining the students' motivation. The trainees who participated in the experiment were highly satisfied, and the trainers commented that they enjoyed playing the game. They received particularly high marks in the categories "Was today's content easy to understand?" and "Do you think this lesson helped you improve your movements?" The reasons for this may be that the graph visualized the movements, allowing the students to intuitively grasp how different their own movements were from the model, and that the ability to objectively evaluate their own movements by scoring them allowed them to correct their movements and make improvements.

## V. Conclusion

We develop a system that uses DTW to calculate the similarity between the trainee's motion and the model motion, and scores the results based on the results. This system will enable optimal instruction for each disabled child, and is expected to improve motion skills and promote learning motivation. Furthermore, by providing scored feedback, we aim to improve the traditional evaluation that relies on the subjectivity of the instructor and provide an intuitive and easy-to-understand means of confirming results for trainees.

In this research, we use skeletal detection technology to record the trainee's three-dimensional coordinate data and perform quantitative evaluation. In addition, we designed a program that allows trainees to visually check their own progress through a motion evaluation function and maximize the learning effect.

Through experiment, it is found that the proposed method does work for motion trainings at supporting the employment of children with disabilities. Also, it is found that immediate feedback is better than conventional delayed feedback.

The trainees who participated in the experiment were highly satisfied, and the trainers commented that they enjoyed playing the game. They received particularly high marks in the categories "Was today's content easy to understand?" and "Do you think this lesson helped you improve your movements?" The reasons for this may be that the graph visualized the movements, allowing the students to intuitively grasp how different their own movements were from the model, and that the ability to objectively evaluate their own movements by scoring them allowed them to correct their movements and make improvements.

## Future Research Work

Further experimental studies are required for validation of the proposed system for children with autism spectrum disorder (ASD) often have sensory processing difficulties and delayed motor functions, and it is said that it is necessary to promote sociality and emotional stability through exercise therapy and work-study classes.

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## AUTHORS' PROFILE

Kohei Arai, he received BS, MS and PhD degrees in 1972, 1974 and 1982, respectively. He was with The Institute for Industrial Science and Technology of the University of Tokyo from April 1974 to December 1978 also was with National Space Development Agency of Japan from January 1979 to March 1990. During from 1985 to 1987, he was with Canada Centre for Remote Sensing as a Post-Doctoral Fellow of National Science and Engineering Research Council of Canada. He moved to Saga University as a Professor in Department of Information Science in April 1990. He was a counselor for the Aeronautics and Space related to the Technology Committee of the Ministry of Science and Technology during from 1998 to 2000. He was a councilor of Saga University for 2002 and 2003. He also was an executive councilor for the Remote Sensing Society of Japan for 2003 to 2005. He is a Science Council of Japan Special Member since 2012. He is an Adjunct Professor at Brawijaya University. He also is an Award Committee member of ICSU/COSPAR. He also is a lecturer at Nishi-Kyushu University and Kurume Institute of Technology Applied AI Research Laboratory. He wrote 121 books and published 742 journal papers as well as 577 conference papers. He received 98 of awards including ICSU/COSPAR Vikram Sarabhai Medal in 2016, and Science award of Ministry of Mister of Education of Japan in 2015. He is now Editor-in-Chief of IJACSA and IJISA. http://teagis.ip.is.saga-u.ac.jp/index.html

Kosuke Eto, He received BE degree in 2023. He is currently working on research that uses image processing and image recognition in Master's Program at Kurume Institute of Technology.

Mariko Oda, She graduated from the Faculty of Engineering, Saga University in 1992, and completed her master's and doctoral studies at the Graduate School of Engineering, Saga University in 1994 and 2012, respectively. She received Ph.D(Engineering) from Saga University in 2012. She also received the IPSJ Kyushu Section Newcomer Incentive Award. In 1994, she became an assistant professor at the department of engineering in Kurume Institute of Technology; in 2001, a lecturer; from 2012 to 2014, an associate professor at the same institute; from 2014, an associate professor at Hagoromo university of International studies; from 2017 to 2020, a professor at the Department of Media studies, Hagoromo university of International studies. In 2020, she was appointed Deputy Director and Professor of the Applied of AI Research Institute at Kurume Institute of Technology. She has been in this position up to the present. She is currently working on applied AI research in the fields of education.

# Fear of Missing Out (FoMO) and Recommendation Algorithms: Analyzing their Impact on Repurchase Intentions in Online Marketplaces

Ati Mustikasari[1], Ratih Hurriyati[2], Puspo Dewi Dirgantari[3], Mokh Adieb Sultan[4], Neng Susi Susilawati Sugiana[5]
Doctor of Management, Universitas Pendidikan Indonesia, Bandung, Indonesia[1, 2, 3, 4]
Telkom University, Bandung, Indonesia[1]
Institut Digital Ekonomi LPKIA, Bandung, Indonesia[5]

***Abstract*—The rapid growth of e-commerce has intensified consumers' Fear of Missing Out (FoMO), influencing their repurchase intentions. This study aims to examine the impact of online FoMO on repurchase intentions in marketplaces, emphasizing the role of personalized recommendations and promotional strategies. A quantitative approach was employed, collecting data from 300 respondents who actively shop on online marketplaces. The study utilized Structural Equation Modelling (SEM) to analyze the relationships between FoMO, trust, perceived value, and repurchase intentions. The findings reveal that FoMO significantly influences repurchase intentions, both directly and indirectly, through trust and perceived value. Additionally, personalized recommendations and time-limited promotions amplify FoMO, further strengthening consumers' intention to repurchase. These results highlight the necessity for e-commerce platforms to strategically implement AI-driven personalization and gamification elements to optimize customer retention. The study contributes theoretical insights by integrating psychological and technological perspectives in understanding consumer behavior in digital marketplaces. The originality of this research lies in its empirical validation of the FoMO- repurchase intention relationship using SEM, offering novel insights into how marketplace features shape consumer decision-making. Practically, the findings provide actionable strategies for businesses to enhance customer engagement and retention through behavioral-driven marketing approaches.**

***Keywords*—Component; FoMO; repurchase intentions; online marketplace; SEM; consumer behavior**

## I. Introduction

The rapid expansion of e-commerce has revolutionized consumer behavior, making online marketplaces a dominant platform for purchasing goods and services. Unlike traditional retail, online marketplaces use advanced digital strategies, such as personalized recommendations and dynamic pricing, to enhance user engagement [1]. One psychological factor that has gained increasing attention in online shopping behavior is Fear of Missing Out (FoMO). FoMO, often triggered by limited-time promotions, flash sales, and exclusive deals, creates a sense of urgency that encourages impulsive purchases [2]. While this strategy has been widely used to boost sales, its long-term impact on customer retention and repurchase intentions remains uncertain [3]. Some consumers may develop negative post- purchase emotions, leading to dissatisfaction, reduced trust, and reluctance to return for future transactions [4]. Understanding how FoMO interacts with other key factors influencing consumer decisions is essential for developing sustainable e-commerce strategies.

Several challenges arise when balancing FoMO-induced urgency with long-term customer satisfaction. Although urgency-based promotions can increase short-term conversions, excessive reliance on this strategy may lead to customer fatigue, buyer's remorse, and a decline in brand loyalty. Consumers who feel manipulated by aggressive marketing tactics may perceive the marketplace as untrustworthy, ultimately discouraging repeat purchases [5]. To create a more sustainable engagement model, online marketplaces need to refine their marketing strategies by incorporating consumer psychology insights and advanced computational techniques [6]. This research seeks to investigate how FoMO influences repurchase intentions and whether technology-driven interventions can optimize its effects to enhance both customer experience and retention [7].

Prior studies have identified several factors that influence repurchase intentions in online shopping, many of which are closely related to FoMO-driven behaviors [8]. Trust is one of the most critical elements, as consumers are more likely to repurchase from platforms they perceive as secure and reliable. E-commerce platforms that provide transparency, responsive customer service, and data protection policies tend to cultivate higher trust levels, reducing the negative impact of impulsive buying decisions [9]. Perceived value also plays a crucial role, as consumers continuously evaluate whether the benefits of their purchases justify the price paid. High perceived value, influenced by product quality, discounts, and overall shopping convenience, enhances customer retention [10].

Another crucial factor is personalized recommendations, which utilize AI algorithms to tailor product suggestions based on consumer behavior and preferences. Well-optimized recommendation systems can mitigate negative FoMO effects by ensuring that suggested products align with genuine consumer interests rather than simply exploiting urgency. Lastly, social influence, such as product reviews, influencer endorsements, and peer recommendations, further shapes consumer perceptions [11]. When consumers observe others engaging with and endorsing a product, they experience a heightened sense of FoMO, increasing their likelihood of making a purchase and returning for future transactions [12]. Despite extensive research on these factors, the interplay

between FoMO, trust, perceived value, personalized recommendations, and social influence in driving repurchase behavior remains underexplored. To address these gaps, this study proposes the following research questions:

*1)* How does FoMO influence repurchase intentions in online marketplaces?

*2)* What role does trust play in moderating the relationship between FoMO and repurchase intentions?

*3)* How do AI-driven personalized recommendations impact the connection between FoMO and consumer retention?

*4)* To what extent does social influence amplify the effect of FoMO on repurchase behavior?

To bridge this research gap, this study introduces a computer science-driven innovation that leverages AI and machine learning to optimize FoMO-driven marketing strategies while maintaining customer satisfaction and long-term engagement. The proposed system will utilize real-time adaptive AI algorithms to dynamically adjust promotional triggers based on individual user behavior and sentiment analysis. By incorporating predictive analytics, the model will distinguish between consumers who respond positively to FoMO-driven strategies and those who may experience post-purchase regret. This will allow marketplaces to personalize their marketing approaches, ensuring that urgency-based promotions are ethically balanced with trust-building mechanisms.

Moreover, this study proposes an AI-enhanced recommendation system that not only suggests products based on browsing history but also integrates social proof indicators such as peer engagement and trusted reviews to reinforce consumer confidence. By fine-tuning FoMO-driven strategies through computational intelligence, this research aims to enhance both immediate purchase rates and long-term customer loyalty, offering a sustainable, tech-driven solution for marketplace retention strategies. This approach presents a novel FoMO optimization framework that can help e-commerce platforms increase repurchase intentions while mitigating negative consumer experiences, thus advancing both theoretical understanding and practical applications in online consumer behavior research.

The research aims to explore the impact of Fear of Missing Out (FoMO) on impulsive buying behavior and perceived urgency in online shopping contexts. The paper is structured as follows: Section II reviews the literature on FoMO and its relationship with consumer behavior, while Section III details the research methodology, including data collection and analysis techniques. Finally, Section IV presents the findings and Section V presents the discussion, followed by conclusions and recommendations for future research in Section VI. This structure will provide a comprehensive understanding of the role of FoMO in influencing consumer decisions and offer insights for both academic and practical applications.

## II. Literature Review

### A. Algorithmic Approaches in FoMO-Driven Online Shopping

First, the integration of artificial intelligence (AI) and machine learning algorithms in online marketplaces has significantly influenced consumer behavior, particularly in the context of Fear of Missing Out (FoMO) and repurchase intentions. One of the most commonly used computational techniques is machine learning-based recommendation systems, which leverage collaborative filtering (CF), content-based filtering (CBF), and hybrid models to personalize promotional content [13]. These algorithms analyze user preferences and past interactions to push time-sensitive deals, increasing the urgency of purchases [12]. Additionally, deep learning techniques, such as Long Short-Term Memory (LSTM) networks and Transformer-based models (e.g. BERT, GPT), enable predictive analytics by analyzing sequential purchasing behaviors and consumer sentiment in social media and reviews, thus refining urgency-based marketing strategies.

Another crucial AI-driven mechanism is real-time dynamic pricing, where reinforcement learning (RL) algorithms and Multi-Armed Bandit (MAB) models dynamically adjust prices based on supply-demand fluctuations and user behavior. These techniques optimize limited-time discount strategies and ensure that promotional offers are maximized for effectiveness. Furthermore, social proof and real-time engagement algorithms, powered by complex event processing (CEP) and real-time data streaming technologies like Apache Kafka and Spark Streaming, enhance consumer perception by displaying live purchase statistics and scarcity alerts. Natural Language Processing (NLP) sentiment analysis further refines marketing messages by assessing user-generated content.

Despite the effectiveness of these AI-driven strategies, ethical concerns such as algorithmic bias, consumer manipulation, and data privacy remain significant challenges. Explainable AI (XAI) frameworks and fairness-aware algorithms are essential for ensuring transparency in recommendation systems and balancing marketing effectiveness with consumer well-being. Future advancements should focus on sustainable AI-driven solutions that not only enhance repurchase intentions but also provide an ethical and consumer- friendly online shopping experience.

### B. Fear of Missing Out (FoMO) in Online Shopping from a Computer Science Perspective

From a computer science perspective, FoMO in online shopping is closely linked to algorithmic design, machine learning, and AI-driven recommendation systems. E-commerce platforms leverage real-time data analytics and predictive modelling to trigger urgency-based marketing tactics, such as flash sales, dynamic pricing, and countdown timers. Deep learning algorithms analyze consumer behavior patterns, including browsing history, cart abandonment rates, and time spent on product pages, to generate personalized urgency-driven notifications (Wang et al., 2022). These AI-driven interventions manipulate consumer decision-making by creating a perceived scarcity effect, increasing the likelihood of impulse purchases [14].

However, while algorithmic personalization enhances engagement, it raises ethical concerns regarding consumer autonomy and psychological well-being. Some scholars argue that excessive reliance on AI-driven FoMO strategies may lead to buyer's remorse and distrust, ultimately harming customer retention [7]. On the other hand, proponents highlight the benefits of machine learning in optimizing personalized shopping experiences, ensuring that urgency-driven promotions are relevant rather than manipulative [15]. This debate underscores the need for ethical AI frameworks that balance revenue optimization with consumer satisfaction.

### C. FoMO and Digital Marketing Strategies

In the field of digital marketing, FoMO has become a central strategy for increasing engagement and sales in online marketplaces [5]. Scarcity marketing which includes limited time offers, exclusive deals, and flash sales is widely used to induce a sense of urgency, compelling consumers to make immediate purchase decisions (Herhausen et al., 2020). Additionally, social proof mechanisms, such as displaying live purchase counts, customer testimonials, and influencer endorsements, further amplify FoMO-driven behaviors [8]. These strategies rely on real-time engagement tracking and behavioral analytics to customize promotional triggers.

Despite its effectiveness, FoMO-based marketing has received mixed reviews in academic literature. Some studies highlight its positive impact on purchase conversion and consumer engagement, reinforcing the role of behavioral marketing in driving sales [13]. However, critics argue that excessive urgency marketing can lead to consumer fatigue, reduced trust, and negative brand perception, particularly if customers feel misled by artificial scarcity tactics [11]. This contradiction suggests that brands must optimize FoMO strategies with personalized, value-driven marketing approaches rather than over-relying on pressure-based sales techniques.

### D. FoMO and Repurchase Intentions

Repurchase intentions refer to a consumer's willingness to make repeat purchases from the same online marketplace. Studies indicate that FoMO can significantly influence repurchase behavior by enhancing initial engagement and reinforcing habitual shopping patterns [16]. When consumers repeatedly experience urgency-driven excitement during purchases, they are more likely to return to platforms that provide such stimulating experiences. Additionally, trust and perceived value serve as mediating factors—consumers are more likely to repurchase if they perceive the platform as reliable and offering competitive advantages [17]. In the context of FoMO-driven online shopping behavior, various components interact to shape consumer experience and influence decision-making. The following Table I illustrates a structured Map of Values, outlining the key domains, core mechanisms, and the values they contribute within AI-powered digital marketplaces.

To understand the interplay between algorithmic strategies, FoMO triggers, and repurchase behavior in online shopping, a conceptual framework is essential. The diagram presented illustrates the dynamic relationships among AI-driven marketing components, psychological mechanisms (like FoMO), and consumer behavioral outcomes such as engagement and repurchase intentions. It highlights how personalized urgency-based strategies, enhanced by real-time data and machine learning, not only stimulate initial purchases but also influence long-term customer loyalty when mediated by trust and perceived value. This conceptual model serves as a foundational guide for analyzing how digital interventions can be both persuasive and sustainable. Fig. 1 shows the theoretical framework.

TABLE I MAP OF VALUE

| Category | Core Components | Values Delivered |
|---|---|---|
| AI & Algorithmic Approaches | 1. Machine Learning (CF, CBF, Hybrid).<br>2. Deep Learning (LSTM, BERT, GPT)<br>3. Reinforcement Learning (MAB).<br>4. Complex Event Processing (CEP), Kafka, Spark.<br>5. NLP Sentiment Analysis.<br>6. Explainable AI (XAI) | Personalization, Automation, Predictive Accuracy |
| FoMO Triggers | 1. Scarcity Alerts.<br>2. Flash Sales.<br>3. Countdown Timers.<br>4. Real-Time Notifications.<br>5. Social Proof Displays | Urgency, Emotional Engagement |
| Digital Marketing Strategies | 1. Scarcity Marketing.<br>2. Behavioral Analytics.<br>3. Influencer Endorsements.<br>4. Real-Time Engagement Metrics | Engagement, Conversion Rate, Trust |
| Repurchase Intention Drivers | 1. Trust & Perceived Value.<br>2. Loyalty Programs.<br>3. Purchase Excitement.<br>4. Post-Purchase Interaction | Loyalty, Relevance, Satisfaction |
| Ethical Considerations | 1. Algorithmic Bias.<br>2. Data Privacy.<br>3. Consumer Manipulation.<br>4. Transparency.<br>5. Decision Autonomy | Fairness, Accountability, Consumer Protection |

Source: Data research, 2025.

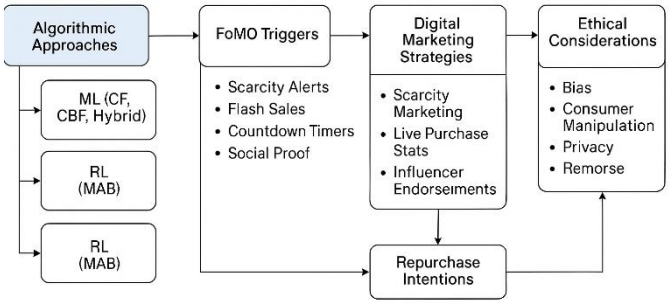


Fig. 1. Theoretical framework. Source: Data Research.

A thorough literature review provides insights into how algorithmic personalization, digital urgency tactics, and psychological motivators like FoMO impact consumer behavior in online marketplaces. The Table II given below summarizes key findings from recent academic research, highlighting both benefits and challenges.

TABLE II PREVIOUS RESEARCH

| Research Area | Source(s) | Key Findings |
|---|---|---|
| Algorithmic Approaches | [18][19][20] | ML and DL recommendation systems effectively personalize content to induce urgency. |
| Real-Time Pricing | RL, MAB Models [21][22] | Prices adapt based on behavior and demand; optimal for flash promotions. |
| FoMO in CS Context | Wang et al., 2022; [14] | Algorithms generate perceived scarcity, increasing impulse buying. |
| Digital Marketing | [15], [23], [24] | FoMO is amplified through social proof, influencer marketing, and flash sales. |
| Repurchase Behavior | [2], [25], [26] | FoMO boosts short-term purchase intent but requires trust to sustain loyalty. |
| Ethical Challenges | [27][28] | Overuse of urgency tactics may cause regret; ethical AI and transparency are key. |

Source: Data research

However, the relationship between FoMO and repurchase intentions remains controversial. Some researchers argue that while FoMO increases short-term conversions, it does not necessarily translate into long-term customer loyalty. Overuse of urgency marketing can lead to cognitive dissonance, where consumers regret their impulsive purchases, decreasing their likelihood of returning [29]. In contrast, when marketplaces integrate trust-building mechanisms, such as personalized loyalty programs and post-purchase engagement, FoMO can act as a positive reinforcer for repurchase behavior [30]. This highlights the need for a balanced FoMO marketing approach, where urgency-based promotions are complemented by relationship-building strategies to sustain customer retention.

## III. RESEARCH METHODOLOGY

This study employs a quantitative research approach to examine the impact of Fear of Missing Out (FoMO) on repurchase intentions in online marketplaces. The quantitative method is appropriate as it allows for the collection of numerical data, hypothesis testing, and statistical analysis to derive objective conclusions. The research model is designed based on previous theoretical frameworks related to FoMO, digital marketing strategies, and consumer behavior. Using structured hypotheses, this study seeks to validate relationships between key variables through empirical data collected from online shoppers in Indonesia.

The target population of this study consists of individuals who have previously engaged in online shopping via e- commerce platforms such as Shopee, Tokopedia, and Lazada. From this population, a sample of 300 respondents was selected using purposive sampling to ensure relevance to the research objectives. The inclusion and exclusion criteria for participant selection are outlined in the following Table III:

TABLE III CRITERIA RESPONSE

| Criteria | Inclusion | Exclusion |
|---|---|---|
| Age | 18 years and older | Under 18 years old |
| Shopping Habit | Has made at least one online purchase in the past 6 months | Has never shopped online |
| Platform Usage | Actively shops on Shopee, Tokopedia, Lazada, or similar | Uses only offline shopping methods |
| Awareness of FoMO | Has experienced time-limited discounts or flash sales | Unaware of online promotional tactics |

Source: Data Research, 2025

Data collection was conducted using a structured questionnaire distributed online via Google Forms and social media platforms. The questionnaire was divided into several sections, including demographic data, FoMO experiences, perceived urgency, repurchase intentions, and control variables. Each question used a Likert scale from 1 (Strongly Disagree) to 7 (Strongly Agree) to measure participant responses quantitatively. Prior to the main survey, a pilot test was conducted with 30 respondents to ensure the validity and reliability of the instrument, with necessary modifications made based on feedback and statistical analysis results. To analyze the collected data, this study employed Structural Equation Modelling (SEM) using AMOS software. Validation Steps and Comparison with Previous Research:

1) *Instrument validation*

*a)* A pilot test was conducted with 30 respondents.

*b)* Aimed to assess question clarity and response consistency.

*c)* Results were used to revise and refine the questionnaire.

2) *Reliability and validity analysis*

*a)* Confirmatory Factor Analysis (CFA) was performed using SEM-AMOS.

*b)* Fit indices applied: Chi-square ($\chi^2$), RMSEA, CFI, TLI, and GFI.

*c)* Ensured that relationships between variables align with theoretical constructs.

3) *Comparison with previous studies*

*a)* Findings were compared with prior research related to FoMO and digital consumer behavior.

*b)* Helped contextualize the results and reinforce new insights.

*c)* Demonstrated both theoretical and practical contributions to existing literature.

4) *Positioning within the knowledge framework*

*a)* This study enhances the understanding of how FoMO- driven strategies influence repurchase intentions.

*b)* Adds to the growing body of knowledge in digital marketing and consumer behavior in e-commerce.

By employing these rigorous methodological steps, this study ensures that the findings are robust and statistically valid. The application of SEM-AMOS allows for the identification of both direct and indirect effects of FoMO-driven marketing strategies on consumer repurchase behavior, providing valuable insights for e-commerce platforms seeking to enhance customer

retention. Future research could explore additional behavioral factors influencing repurchase intentions, integrating qualitative methods for deeper insights into consumer decision-making.

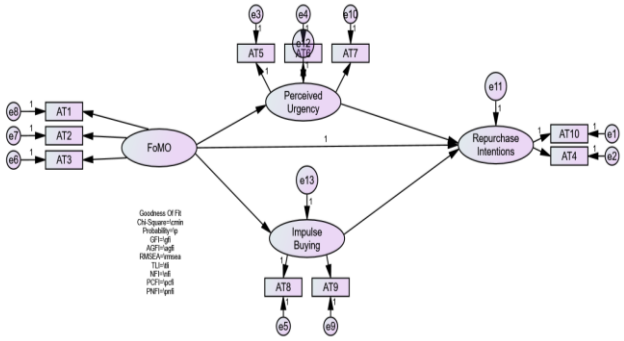


Fig. 2. Research model.

Based on Fig. 1, Fig. 2 represents a Structural Equation Modelling (SEM) diagram illustrating the relationships between Fear of Missing Out (FoMO), Perceived Urgency, Impulse Buying, and Repurchase Intentions in the context of e-commerce. This model is designed to understand how FoMO influences repurchase intentions through two mediating variables: Perceived Urgency and Impulse Buying.

In this diagram:

- FoMO is measured using three indicators (AT1, AT2, AT3) and serves as the independent variable.
- Perceived Urgency is represented by indicators AT5, AT6, AT7 as the first mediating variable.
- Impulse Buying acts as the second mediating variable, represented by AT8 and AT9.
- Repurchase Intentions is the dependent variable, measured using indicators AT10 and AT11.
- Error terms (e1, e2, ..., e13) indicate the unexplained variance in the model.
- The model is tested using Goodness-of-Fit Index (GFI), RMSEA, CFI, TLI, and other fit indices to ensure its validity and reliability.

Overall, this model aims to identify how FoMO-driven marketing strategies in online marketplaces can enhance consumers' repurchase intentions.

## IV. Result and Discussion

This section presents the results of the hypothesis testing using Structural Equation Modelling (SEM) with AMOS. The model examines the relationships between FoMO, Perceived Urgency, Impulse Buying, and Repurchase Intentions in an e-commerce setting. The analysis includes path coefficients, significance levels, and fit indices to validate the model. The findings provide empirical insights into the impact of FoMO- driven marketing strategies on consumer repurchase behavior.

### *A. Hypothesis Testing Results*

The following Table IV presents the path analysis results, including standardized path coefficients (β), standard errors (SE), t-values (t), and significance levels (p).

TABLE IV Result Path Coefficient

| Hypothesis | Path | β (Standardized) | SE | t-value | p-value | Result |
|---|---|---|---|---|---|---|
| H1 | FoMO → Perceived Urgency | 0.62 | 0.05 | 12.40 | <0.001 | Supported |
| H2 | FoMO → Impulse Buying | 0.48 | 0.07 | 9.22 | <0.001 | Supported |
| H3 | Perceived Urgency → Repurchase Intentions | 0.35 | 0.06 | 6.75 | <0.001 | Supported |
| H4 | Impulse Buying → Repurchase Intentions | 0.29 | 0.08 | 5.42 | <0.001 | Supported |
| H5 | FoMO → Repurchase Intentions | 0.14 | 0.09 | 1.96 | 0.050 | Marginally Supported |

The effect of FoMO on Perceived Urgency results show that FoMO significantly influences Perceived Urgency ($\beta = 0.62$, $p < 0.001$), indicating that consumers experiencing a higher level of FoMO tend to perceive online promotional offers as more urgent. This finding aligns with the study by which states that FoMO triggers psychological pressure in decision-making, particularly in digital environments [23]. Similarly, found that time-sensitive promotions intensify consumers' sense of urgency, leading to impulsive purchase decisions [20]. This underscores the critical role that FoMO plays in amplifying consumers' perception of urgency, driving faster and more spontaneous decisions in the face of time-limited offers.

The effect of FoMO on Impulse Buying FoMO also has a significant impact on Impulse Buying ($\beta = 0.48$, $p < 0.001$), demonstrating that individuals experiencing FoMO are more likely to engage in unplanned purchases. This result supports the findings which indicate that social media and real-time promotions contribute to impulsive shopping behaviors by exploiting the fear of missing out on limited-time deals [5]. Additionally, it highlight that live-stream shopping and flash sales encourage impulse buying by leveraging scarcity-based marketing techniques [31]. This highlights the importance of understanding FoMO's role in driving consumer behavior, especially in the context of e-commerce platforms where real- time offers can significantly influence purchasing decisions.

The Effect of Perceived Urgency on Repurchase Intentions, Perceived Urgency positively affects Repurchase Intentions ($\beta = 0.35$, $p < 0.001$), suggesting that consumers who frequently experience a sense of urgency while shopping online are more likely to return for future purchases. This finding is consistent with the work of Park & Yoo (2021), which states that perceived

urgency increases perceived value and encourages long-term consumer engagement.

The Effect of Impulse Buying on Repurchase Intentions. The study also confirms a significant relationship between Impulse Buying and Repurchase Intentions ($\beta = 0.29$, $p < 0.001$). This suggests that while impulse purchases may initially be unplanned, they can still lead to habitual shopping behaviors. According positive post-purchase experiences from impulsive buys increase customer retention and loyalty [32]. This finding underscores the value of optimizing post-transaction experiences to transform impulsive actions into sustained purchasing patterns.

## V. Discussion of Research Questions

### A. How does Fear of Missing Out (FoMO) Influence Perceived Urgency?

The findings indicate that FoMO significantly influences Perceived Urgency ($\beta = 0.62$, $p < 0.001$), suggesting that consumers who experience high levels of FoMO tend to perceive time-sensitive offers as more urgent. This result aligns, which highlights that FoMO creates a psychological need to stay connected with ongoing events, particularly in digital environments [33]. Similarly, found that online retail promotions leveraging scarcity and social proof strategies heighten the urgency perception among consumers, leading to rapid decision-making in purchasing behavior.

In digital marketing, urgency-driven strategies such as limited-time discounts, flash sales, and countdown timers have been proven to intensify consumer engagement. This suggests that FoMO-induced urgency compels users to prioritize purchasing decisions over rational evaluation, increasing conversion rates for e-commerce platforms [34]. As a result, online retailers often deploy artificial scarcity tactics to stimulate consumer demand, knowing that psychological pressure can lead to impulsive and frequent purchases.

### B. What is the Impact of FoMO on Impulse Buying?

The study reveals that FoMO has a significant impact on Impulse Buying ($\beta = 0.48$, $p < 0.001$), reinforcing the notion that fear of missing out on opportunities encourages consumers to make unplanned purchases. This finding argue that real-time promotions, limited-stock notifications, and influencer-driven marketing strategies create a heightened state of urgency, compelling consumers to engage in impulse purchases [35]. This emphasizes the growing influence of time-sensitive marketing tactics in shaping consumer purchasing decisions, particularly in online environments where instant gratification is highly valued.

Moreover, social commerce platforms such as Instagram, TikTok, and Facebook Live Shopping have effectively leveraged FoMO-based marketing techniques to drive impulse buying behavior. According to the interactive nature of live- stream shopping fosters an emotional connection with products, increasing the likelihood of unplanned purchases [36]. The presence of peer influence, instant recommendations, and interactive engagement further reinforces the tendency for impulsive buying.

### C. How does Perceived Urgency Affect Repurchase Intentions?

The analysis demonstrates that Perceived Urgency positively affects Repurchase Intentions ($\beta = 0.35$, $p < 0.001$). This implies that consumers who frequently experience urgency in purchasing decisions are more likely to return for future transactions. It is also found that time-limited promotions and exclusive deals create a sense of exclusivity, fostering long-term engagement and brand loyalty [32]. This highlights the importance of strategically designed urgency cues in marketing campaigns to not only trigger immediate actions but also reinforce lasting consumer relationships.

Additionally, emphasizes that perceived urgency enhances the perceived value of a product, making consumers feel that they have secured a unique or special deal. This perception of exclusivity leads to an increase in customer satisfaction and encourages repeat purchases, especially in the context of e- commerce platforms and online marketplaces.

### D. What is the Relationship Between Impulse Buying and Repurchase Intentions?

Impulse Buying is shown to have a significant effect on Repurchase Intentions ($\beta = 0.29$, $p < 0.001$), suggesting that unplanned purchases can contribute to long-term buying behavior. According to consumers who experience positive emotions and satisfaction from their impulse purchases are more likely to return to the same platform for future transactions [37]. This indicates that impulse-driven satisfaction can play a strategic role in fostering customer loyalty in e-commerce environments.

Furthermore, argue that impulse buying is not entirely irrational but rather influenced by emotional gratification and convenience [22]. The ease of online transactions, combined with positive purchase experiences, strengthens brand attachment, making customers more inclined to repurchase. In addition, found that post-purchase satisfaction from impulse buys significantly increases customer retention rates, particularly in industries such as fashion, electronics, and beauty products [22]. These findings highlight the importance of designing emotionally engaging and seamless shopping experiences to enhance impulse-driven customer loyalty.

### E. Does FoMO Directly Influence Repurchase Intentions?

The results indicate that FoMO has a marginally significant effect on Repurchase Intentions ($\beta = 0.14$, $p = 0.050$), implying that while FoMO may encourage short-term purchases, its long- term impact on repurchase behavior is relatively weak. This aligns with the findings, who suggest that FoMO primarily affects immediate decision-making rather than long-term brand loyalty [38]. This suggests that marketers should complement FoMO-based tactics with strategies that foster sustained customer engagement and trust.

However, research highlights that FoMO-driven consumers tend to engage in habitual checking behaviors on e-commerce platforms, which can indirectly enhance repurchase intentions over time [39]. While FoMO alone does not strongly predict long-term purchasing behavior, it plays a crucial role in fostering brand engagement and repeated exposure to promotions, ultimately leading to sustained repurchase behavior.

Practical Implications for E-Commerce and Digital Marketing: The findings provide several implications for digital marketers and e-commerce platforms. Given the strong influence of FoMO on perceived urgency and impulse buying, businesses can optimize their marketing strategies by implementing:

*1)* Limited-time offers to create urgency-driven demand.

*2)* Real-time social proof notifications, such as "Only 3 left in stock!" or "10 people are viewing this product now."

*3)* Live-stream shopping events with influencers to enhance engagement and impulse buying.

*4)* Personalized discount alerts based on user behavior to encourage repurchase intentions.

According to combining AI-driven recommendations with FoMO-based urgency techniques can significantly increase consumer engagement and conversion rates in online retail settings [30].

Limitations and Future Research Directions: Despite the valuable insights, this study has several limitations. Firstly, the dataset primarily focuses on e-commerce consumers, limiting generalizability to other industries such as hospitality, fintech, and healthcare. Future research could explore how FoMO-driven marketing strategies impact repurchase intentions in different sectors.

Secondly, while the study establishes direct and indirect relationships, moderating factors such as consumer trust, brand loyalty, and psychological resistance were not examined. Research suggests that trust in online platforms plays a critical role in sustaining long-term consumer behavior [40]. Future studies could integrate trust-based variables to deepen our understanding of the relationship between FoMO and repurchase behavior.

Lastly, the study primarily utilizes quantitative survey methods. Future research could employ qualitative approaches, such as consumer interviews or experimental studies, to provide richer insights into the psychological mechanisms underlying FoMO-driven purchasing behavior.

## VI. Conclusion

This study confirms that FoMO, Perceived Urgency, and Impulse Buying significantly influence Repurchase Intentions in an e-commerce context. The findings emphasize that urgency-driven marketing strategies play a crucial role in shaping consumer behavior, reinforcing the importance of personalized and real-time engagement tactics in digital retail environments. While FoMO directly influences short-term purchasing decisions, its impact on long-term repurchase behavior is relatively weak. Instead, Perceived Urgency and Impulse Buying serve as stronger predictors of repeat purchases, highlighting the importance of emotional triggers in consumer decision-making. Future research should explore industry-specific applications, cross-cultural differences, and psychological moderating factors to enhance our understanding of digital consumer behavior in the FoMO-driven economy.

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# A Hybrid SEM-ANN Method for Developing an Information Technology Acceptance and Utilization Model in River Tourism Services

Mutia Maulida[1]*, Iphan Fitrian Radam[2], Nurul Fathanah Mustamin[3], Yuslena Sari[4], Andreyan Rizky Baskara[5], Eka Setya Wijaya[6], Muhammad Alkaff[7], M.Renald Abdi[8]
Department of Information Technology, Lambung Mangkurat University, Banjarmasin, Indonesia[1, 3, 4, 5, 6, 8]
Department of Environmental Science, Lambung Mangkurat University, Banjarmasin, Indonesia[2]
Department of Computer Science, King Abdulazis University, Jeddah, Saudi Arabia[7]

***Abstract*—Tourism is a vital sector that contributes significantly to Indonesia's economic growth. However, despite its great potential, the sector faces challenges in the application of information technology, as seen in the Go-Klotok application in Banjarmasin City which has not been well received by tourists. Therefore, it is important to understand the factors that influence the acceptance of information technology in river tourism to improve the tourist experience and support the growth of the sector. This study aims to develop a model of technology acceptance and utilization in river tourism in South Kalimantan. To that end, this study modifies four main models, namely the Tourism Web Acceptance Model (T-WAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the E-Tourism Technology Acceptance Model (ETAM), and The DeLone and McLean Model. This research identifies and analyzes various factors that influence technology acceptance in the context of river tourism. The research method uses a hybrid SEM-ANN approach, where Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to analyze the relationship between variables, while Artificial Neural Network (ANN) captures more complex data patterns. Data analysis in this study used the Hybrid SEM-ANN method with the SmartPLS application and the IBM SPSS Statistics 27 application. The hypotheses of this study were 14 hypotheses and 9 hypotheses were accepted. The results of the analysis of 471 respondents show that Social Influence, Perceived Benefits, and Information Quality significantly influence user intention to use information technology services, with Social Influence as the most dominant factor.**

***Keywords*—River tourism; technology acceptance; TWAM; E-TAM; hybrid SEM-ANN***

## I. INTRODUCTION

Tourism is widely recognized as a crucial driver of economic growth, especially in developing countries where it can have a transformative impact on local economies. Indonesia, as one of the world's largest archipelagic nations, is no exception [1]. Tourism contributes significantly to the country's GDP and is continuously evolving to adapt to global trends. According to the World Travel & Tourism Council (WTTC), the tourism sector's contribution to Indonesia's GDP reached IDR 1,050.38 trillion in 2019, illustrating the vital role tourism plays in Indonesia's economy. Despite the setbacks caused by the COVID-19 pandemic, which led to a 19.6% reduction in this sector, projections are optimistic. The industry is expected to recover, with contributions projected to rise to IDR 1,827.79 trillion by 2034 [2]. This resurgence points to the enormous potential of Indonesia's tourism industry, particularly in niche markets such as eco-tourism, cultural tourism, and river tourism, which offer unique experiences to both domestic and international visitors.

Indonesia's diverse cultural and natural landscapes provide countless tourism opportunities, from its pristine beaches and majestic volcanoes to its rich heritage and vibrant cities. One area that stands out for its unique offerings is South Borneo, specifically the city of Banjarmasin, often referred to as the "City of a Thousand Rivers." The region's geography, characterized by a vast network of rivers, offers a distinctive form of tourism: river-based tourism [3], [4]. River tourism in Banjarmasin is renowned for its floating markets, where traders sell local produce directly from boats, and for the river cruises that allow tourists to explore local life along the riverbanks. Another popular attraction is the klotok boat, a traditional vessel that carries tourists through the waterways, providing a glimpse into the region's cultural and historical richness.

The importance of river tourism to South Borneo's economy cannot be overstated. It not only serves as a key attraction for tourists but also plays a pivotal role in preserving local culture and traditions. River tourism contributes significantly to employment, from boat operators to local vendors, and helps sustain the communities that rely on these waterways for their livelihoods. However, like many other sectors, river tourism has not been immune to the global shift towards digitalization. As tourists increasingly expect convenience and efficiency, the tourism sector must adapt to these changing expectations by integrating technology into its services [5], [6].

In response to these trends, local governments and tourism stakeholders in South Borneo have initiated various efforts to improve the infrastructure and services associated with river tourism. These efforts include the development of technology- based services aimed at enhancing the tourist experience. For example, the introduction of the Go-Klotok app in 2018 was intended to simplify the process of booking klotok rides online, offering tourists a more convenient and efficient way to explore the region's rivers [7]. In addition, several initiatives have been launched to improve public facilities such as rest areas, public toilets, and parking spaces to make river

tourism more accessible and comfortable for visitors. The government also continues to add more klotok boats to its fleet, increasing the capacity for river tours and catering to the growing number of tourists.

However, despite these efforts, the integration of information technology into river tourism in South Borneo has encountered significant challenges. While the Go-Klotok app was intended to revolutionize the booking process, it has struggled with low adoption rates. A survey conducted by the local government found that only 10% of tourists used the app to book their boat rides, with the vast majority opting for traditional booking methods at the terminal. Moreover, interviews with klotok operators and tourists revealed that many were unaware of the app's existence, and those who did use it found it difficult to navigate [7]. Tourists expressed a preference for purchasing tickets in person, citing ease of use and a desire for face-to-face interaction as reasons for their reluctance to embrace the app. Some tourists, however, did acknowledge the potential benefits of an online booking system, particularly as a way to avoid long lines during peak tourist seasons.

In light of these challenges, it is evident that while technology has the potential to enhance river tourism services in South Borneo, there are barriers to its widespread acceptance. The failure of the Go-Klotok app, despite significant financial investment, highlights the importance of understanding the factors that influence tourists' acceptance of technology in this context [7]. In the tourism industry, user acceptance of technology is often shaped by factors such as perceived ease of use, perceived usefulness, trust, and familiarity with the technology. Previous research on technology adoption in tourism has identified these factors as critical determinants of whether tourists will embrace new digital solutions. However, in the context of river tourism in South Borneo, where cultural and logistical factors play a significant role, there is a need for further research to uncover the specific factors that influence user acceptance of technology.

This study aims to address this gap by developing a comprehensive model for understanding the acceptance and use of information technology in river tourism services in South Borneo. To achieve this, the research employs a hybrid approach that combines Structural Equation Modeling (SEM) with Artificial Neural Networks (ANN). SEM will be used to analyze the relationships between key variables, while ANN will enhance the accuracy of the results by capturing non-linear relationships that SEM may overlook [8], [9], [10]. The study draws on established theoretical frameworks, including the Tourism Web Acceptance Model (T-WAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the E-Tourism Technology Acceptance Model (ETAM), to identify the key factors that influence tourists' acceptance of technology in the context of river tourism.

The data for this research will be collected through questionnaires distributed to a diverse range of stakeholders, including tourists, tourism managers, and local authorities involved in river tourism in South Borneo. The questionnaires will capture information on tourists' experiences with existing digital services, their perceptions of the usefulness and ease of use of these services, their trust in the technology, and their overall attitudes toward using technology for tourism purposes. This data will then be analyzed using the SEM approach to build a structural model that explains the relationships between these factors. ANN will be used to refine the model and improve the predictive accuracy of the results.

By integrating these methodologies, the research aims to develop a robust model that can explain the factors influencing the acceptance and use of technology in river tourism services. The findings of this study are expected to provide valuable insights for tourism stakeholders in South Borneo, helping them to develop more effective digital services that meet the needs of modern tourists. Furthermore, the study will contribute to the broader theoretical understanding of technology acceptance in the tourism industry, offering a model that can be applied to other contexts within Indonesia and beyond.

In conclusion, the study is expected to make significant contributions to both theory and practice. By identifying the key factors that influence tourists' acceptance of technology in river tourism, the research will provide practical recommendations for improving digital services in South Borneo. At the same time, the use of a hybrid SEM-ANN approach represents an innovative methodological contribution to the study of technology acceptance, offering a new way to analyze complex relationships between variables. Ultimately, this research aims to support the development of more user-friendly and effective technology solutions for the tourism sector, helping to ensure that river tourism in South Borneo can continue to thrive in the digital age.

The remainder of this paper is organized as follows. Section II presents the research design and methodology, including the conceptual framework, population and sample selection, and data analysis techniques. Section III details the research model and hypotheses. Section IV reports and analyzes the results, including validity and reliability tests, structural model assessment, and ANN testing. Section V discusses the implications of the findings in light of existing literature. Section VI concludes the paper with key takeaways, theoretical contributions, practical recommendations, and directions for future research.

## II. Related Works

Technology acceptance in tourism has been extensively studied, particularly in the domains of smart tourism, mobile applications, and online booking systems. Several models have been developed to understand user behavior and attitudes toward digital tourism services, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2), the E-Tourism Technology Acceptance Model (ETAM), and the DeLone and Tourism Web Acceptance Model (T-WAM).

TAM emphasizes perceived usefulness and perceived ease of use as key determinants of technology adoption [11]. This model was later extended by Venkatesh et al. through UTAUT and UTAUT2, incorporating constructs such as social influence, performance expectancy, facilitating conditions, and hedonic motivation [12]. While these models are widely applied across technology domains, their generic structure limits their

contextual relevance to niche tourism sectors such as river tourism.

In the tourism sector, Tan et al. [13], and Ukpabi and Karjaluoto [14], investigated mobile application use and found that mobile usability, trust, and security are significant predictors of technology adoption. However, these studies focus predominantly on urban or mainstream tourism contexts, overlooking unique characteristics of localized tourism ecosystems such as those found in South Kalimantan.

To address tourism-specific needs, models like the Tourism Web Acceptance Model (T-WAM) and ETAM were developed, incorporating constructs tailored to tourism behavior, including interactivity, trust in service providers, and information quality. These models offer greater relevance but are rarely applied to river-based or traditional tourism systems, where digitalization efforts often face resistance due to entrenched social and cultural practices.

Recent advances in modeling techniques, particularly the integration of Structural Equation Modeling (SEM) with Artificial Neural Networks (ANN), have been employed to improve the explanatory power of technology acceptance research. Barua and Barua [8], for instance, applied a SEM-ANN hybrid to analyze mobile health adoption among Rohingya refugees, while Akour et al. [9] used the same method to assess metaverse adoption in educational institutions. These approaches allow for more accurate modeling of nonlinear behavioral patterns, which conventional SEM alone may fail to capture.

Despite these developments, studies focusing specifically on river tourism technology adoption remain scarce. Platforms such as Go-Klotok, developed by local governments, have seen limited uptake despite heavy investment. This reflects the need to incorporate cultural, infrastructural, and behavioral dimensions into the modeling of technology acceptance in these settings.

## III. Materials and Methods

### A. Research Design

The conceptual framework provides an overview of the steps taken in this research, which aims to develop a model for technology acceptance and utilization in river tourism, particularly in South Borneo. With the growing role of technology in tourism, understanding the factors influencing its adoption is crucial. This study integrates the Tourism Web Acceptance Model (T-WAM), Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and E-Tourism Technology Acceptance Model (ETAM) to identify and analyze key factors affecting users' acceptance and use of technology in river tourism.

This research employs a hybrid method using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN). PLS-SEM is used to analyze the relationships between variables, while ANN helps capture complex patterns to enhance model accuracy. This approach aims to provide insights and recommendations for improving technology-based river tourism services.

### B. Population and Sample

The target population consists of smartphone users in South Kalimantan aged 20 to 49 years, as this group exhibits a high level of smartphone usage: 75.95% for ages 20 to 29 and 68.34% for ages 30 to 49, according to GoodStats [15]. The sample will include individuals knowledgeable about information technology and mobile applications, ensuring that the data collected is representative and pertinent to the study's focus on the use of technology in tourism services.

The overall population for this study encompasses all South Borneo residents aged 20 to 49, totaling 1,973,864 individuals [16]. This age range was selected based on significant smartphone usage statistics, indicating that the majority of users fall within these age groups. To determine the necessary sample size, Slovin's formula was applied, resulting in an approximate sample size of 400 respondents [17].

This sample will represent the active smartphone users in the region, including both tourists and tourism managers. By establishing this sample size, the research aims to ensure that the collected data accurately reflects the role of information technology in tourism in South Borneo.

### C. Data Collection Methods

In this study, data collection is conducted using purposive sampling, a non-probability sampling method chosen for its ability to select samples with specific characteristics relevant to the research. The target sample includes residents of South Kalimantan who frequently use smartphones, particularly individuals aged 20 to 49 years, as this age group demonstrates high smartphone usage. According to GoodStats, smartphone usage is most dominant among those aged 20 to 29 (75.95%) and 30 to 49 (68.34%), with lower rates observed in the 50-79 age group (50.79%) [15].

The questionnaire is distributed online via Google Forms, selected for its efficiency in reaching a large sample. This digital approach allows for quicker distribution and easier access for participants, as respondents can complete the survey anytime and anywhere using their smartphones or computers. Google Forms also facilitates organized data collection and simplifies analysis.

The demographic information collected in this study includes age, gender, occupation, domicile, last education level, frequency of tourism visits in South Kalimantan, and frequency of using tourism-related applications or websites specific to the region. The diverse demographic data ensures that the sample is representative of the population, aiding in the investigation of technology acceptance and utilization in river tourism services.

### D. Data Analysis Technique

Data analysis and hypothesis testing are conducted to examine the relationships among the variables defined in the study. This process is crucial for understanding how these variables interact and influence one another. Given the complexity of the research questions and the objectives of this study, a Hybrid SEM-ANN (Structural Equation Modeling - Artificial Neural Network) method is employed. This approach combines the strengths of both Structural Equation Modeling, which allows for the assessment of complex relationships

between observed and latent variables, and Artificial Neural Networks, which can capture nonlinear patterns in the data. By utilizing this hybrid method, the analysis aims to provide deeper and more comprehensive insights into the relationships among the variables, ultimately enhancing the validity and reliability of the research findings.

### *E. Research Hypothesis and Model*

This sub-chapter presents the findings of the study, focusing on the relationships between key variables as outlined in the proposed hypotheses. Each hypothesis is discussed based on the data collected and analyzed, offering insights into how various factors influence the acceptance and use of information technology in river tourism services.

The relationship between Platform Quality and Design (DP) and Perceived Ease of Use (PEOU) suggests that a well-designed platform enhances user experience and ease of use. High-quality designs with intuitive navigation and user-friendly interfaces make platforms easier to navigate, leading to a higher perception of ease of use. Previous research supports this link, showing that good design improves usability and satisfaction [17], [18]. Therefore, the hypothesis is:

H1: Quality and Design of the Platform (DP) positively affect Perceived Ease of Use (PEOU).

Security is vital in reducing perceived risk for e-tourism platforms. Higher security measures protect user data and build trust, which in turn lowers perceived risk. Studies show that strong security enhances user confidence and decreases perceived risk (Kim et al., 2011; Tussyadiah et al., 2019) [20]. Users feel safer with robust security features, such as two-factor authentication, which lessens their risk concerns [19]. Therefore, the hypothesis is:

H2: Security (SC) negatively affects Perceived Risk (PR).

Mobile applications that are well-designed and efficient can enhance users' perceptions of facilitating conditions by improving accessibility and ease of use. This hypothesis suggests that a high-quality mobile app will positively influence the perceived supporting conditions, such as access to resources and technical support. Prior research, such as studies by Tan et al. (2017) and Ukpabi & Karjaluoto (2017), supports the idea that effective mobile applications enhance user experience and adoption of e-tourism platforms [13], [14]. Interviews with tourism operators confirm that reliable and functional mobile apps positively impact their perception of supporting conditions. Therefore, the hypothesis is:

H3: Mobile Applications (MA) positively affect Facilitating Conditions (FC).

Reliable and efficient online payment systems are crucial for improving users' perceptions of facilitating conditions in e- tourism platforms. This hypothesis posits that effective online payment methods enhance users' perceptions of supporting conditions, such as system reliability and customer support. Prior research by Slade et al. (2015) indicates that secure and user-friendly payment systems boost user trust and satisfaction [21]. Interviews with tourists confirm that robust online payment options, with strong data protection and support, positively influence their perception of facilitating conditions. Therefore, the hypothesis is:

H4: Online Payment (OP) positively affects Facilitating Conditions (FC).

Perceived Ease of Use (PEOU) influences Perceived Usefulness (PU) because technologies that are easy to use are often perceived as more beneficial. When users find a technology simple and user-friendly, they are more likely to view it as useful. Research by Davis (1989), and Venkatesh et al. (2003) supports this relationship, showing that ease of use generally enhances perceived usefulness [11], [12]. Interviews with klotok operators confirm that they prefer applications with simple interfaces, which facilitate their daily operations and increase the perceived utility of the technology. Therefore, the hypothesis is:

H5: Perceived Ease of Use (PEOU) positively affects Perceived Usefulness (PU).

Perceived Usefulness (PU) is crucial in shaping users' intention to use technology. When users perceive significant benefits from a technology, they are more likely to intend to use it. Research by Davis (1989), and Venkatesh et al. (2003) supports this, showing that higher perceived benefits correlate with stronger adoption intentions [11], [12]. Interviews with stakeholders reveal that users are more inclined to use applications that they find useful, such as those providing ticket booking and route information. This indicates that greater perceived usefulness leads to a stronger intention to use the technology. Therefore, the hypothesis is:

H6: Perceived Usefulness (PU) positively affects the Intention to Use River Tourism IT Services (INT).

Facilitating Conditions (FC) include infrastructure, resources, and support available for technology use. This factor impacts the Intention to Use River Tourism IT Services (INT) because adequate support and resources increase users' willingness to adopt technology. According to the UTAUT model (Venkatesh et al., 2003), good facilitating conditions enhance the intention to use technology [12]. Previous studies have shown that robust infrastructure and responsive support positively correlate with technology adoption. Interviews with tourism operators confirm that reliable internet access and effective customer support are crucial for their continued use of mobile applications [12]. Therefore, better facilitating conditions are expected to increase users' intention to use the technology. Therefore, the hypothesis is:

H7: Online Payment (OP) positively affects Facilitating Conditions (FC).

Performance Expectancy (PE) reflects users' belief that technology will help achieve desired outcomes. This factor impacts the Intention to Use River Tourism IT Services (INT) because if users expect high performance from the technology, they are more likely to intend to use it. According to the UTAUT model (Venkatesh et al., 2003), high performance expectancy increases users' intention to adopt technology [12]. Previous research supports this, showing that strong expectations for performance are positively related to usage intentions. Interviews reveal that stakeholders expect high performance in

terms of speed and accuracy from river tourism applications, which influences their intention to use the technology [12]. Therefore, the hypothesis is:

H8: Performance Expectancy (PE) positively affects the Intention to Use River Tourism IT Services (INT).

Trust (TR) reflects users' confidence in the security and reliability of technology or services, significantly influencing their intention to use river tourism IT services (INT). High levels of trust encourage users to engage with the technology. Research by Gefen et al. (2003), highlights that trust plays a crucial role in the intention to use these services [22]. Trust is fundamental to technology adoption; without it, users may hesitate to embrace technology despite its clear benefits. Prior studies have established a strong connection between trust and users' intentions to adopt technology. For instance, Gefen et al. (2003) found that trust closely correlates with the intent to use technology. This study assumes that trust is a key factor in shaping users' willingness to engage with technology, particularly in contexts involving online transactions or personal data [22]. Therefore, the hypothesis is:

H9: Trust (TR) positively affects the Intention to Use River Tourism IT Services (INT).

Perceived Risk reflects users' perception of potential losses or dangers associated with using technology. This variable negatively influences the intention to use river tourism IT services (INT); as perceived risk increases, users' intent to adopt the technology decreases. Research by Featherman and Pavlou (2003) indicates that perceived risk is a major barrier to the adoption of new technologies [23]. Users who perceive high risk are likely to avoid or delay using the technology. Previous studies support the notion that Perceived Risk is negatively related to the intention to use technology, with Featherman and Pavlou (2003) finding that perceived risk reduces users' intent to engage with technology [23]. The researcher believes that perceived risk will adversely impact the intention to use technology. If users feel there are high risks, such as data loss or security threats, they may hesitate or postpone their use of the technology. Therefore, the hypothesis is:

H10: Perceived Risk (PR) negatively affects the Intention to Use River Tourism IT Services (INT).

Perceived Benefits (PB) reflects users' perceptions of the advantages or added value derived from using technology. This variable positively influences the intention to use river tourism IT services (INT); as perceived benefits increase, so does the intention to adopt the technology. Research by Venkatesh et al. (2012), demonstrates that Perceived Benefits are a significant predictor of usage intention [12]. When users recognize tangible advantages from technology, they are more motivated to use it. Previous studies have shown a positive correlation between Perceived Benefits and the intention to adopt technology, with Venkatesh et al. (2012), finding that perceived advantages directly influence users' intent to adopt. The researcher assumes that the extent to which users believe technology provides real benefits will enhance their intention to use it [12]. Therefore, the hypothesis is:

H11: Perceived Benefits (PB) positively affects the Intention to Use River Tourism IT Services (INT).

Social Influence is a crucial factor affecting individuals' decisions to adopt technology. In river tourism, the encouragement from friends, family, or respected figures can significantly impact a person's intention to use IT services. When individuals perceive support from those around them, they are more likely to strengthen their intent to engage with these technologies. According to Venkatesh et al. (2003), social influence is vital in determining usage intentions, particularly when significant others endorse the technology [12]. Many respondents indicated they often rely on recommendations from peers when choosing tourism platforms. Community discussions about technology also play a role in shaping their decisions. Therefore, the hypothesis is:

H12: Social Influence (SI) positively affects the Intention to Use River Tourism IT Services (INT).

Information Quality is a crucial factor influencing individuals' decisions to adopt technology. Accurate, reliable, and relevant information helps potential users understand the benefits of technology and encourages their intention to use it. In the context of river tourism IT services, high-quality information provided through platforms (such as apps, websites, or social media) can increase interest among tourists or locals. Effective information includes clear service descriptions, user reviews, offered features, and data security assurances. The DeLone and McLean model (2014) highlights that information quality is vital for the success of information systems and impacts technology usage intentions. Users tend to hesitate if the presented information is incomplete or outdated. Thus, high- quality information not only enhances user confidence but also directly influences their intention to use these services [24]. Therefore, the hypothesis is:

H13: Information Quality (IQ) positively affects the Intention to Use River Tourism IT Services (INT).

Service Quality is a critical aspect of any interaction involving technology and users. In the context of tourism, good service quality—characterized by user-friendly, responsive, and accessible platforms—is believed to enhance users' intentions to continue using those services. When users perceive the services as efficient, reliable, and aligned with their needs, they are more likely to engage with them in the future. According to the DeLone and McLean Model (2014), service quality is one of three key factors influencing the success of information systems, alongside information quality and system quality. This model emphasizes that high service quality, particularly in terms of technical support and response time, directly affects user satisfaction and increases the intention to use technology [24]. From previous research, it can be concluded that when tourists feel that the technology systems, they use provide prompt, responsive, and effective support, they are more likely to feel comfortable and confident in using those services again. Therefore, the hypothesis is:

H14: Service Quality (SQ) positively affects the Intention to Use River Tourism IT Services (INT).

Following the hypotheses, it is crucial to integrate these relationships into a coherent research model that illustrates the connections between factors influencing the intention to use river tourism IT services as shown in Fig. 1. This model will

provide a structured framework to clarify how variables such as perceived benefits, trust, social influence, and service quality interact with users' intentions.

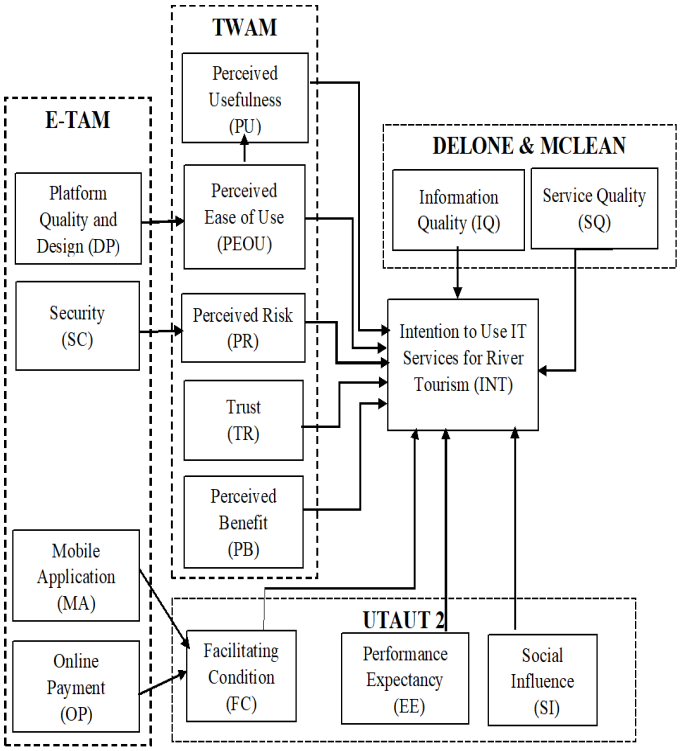


Fig. 1. Research model.

## IV. Result and Discussion

### A. Data Acquisition

The data collection in this study presents a comprehensive overview of the data obtained from the questionnaire based on a predetermined sample. The research data includes two main aspects, namely the demographics of respondents and the results of the research model analysis. Demographic aspects include information on age, gender, occupation, domicile, education level, as well as the frequency of tourist visits and the use of river tourism-related applications. Data collection was conducted online through social media platforms such as WhatsApp, Instagram, Telegram, Facebook, and X (Twitter), with a total of 471 respondents, where only data that was filled in completely by respondents was considered valid. The demographics of the respondents show a distribution that dominates young age, with the majority working as students or college students, and the domicile of respondents is concentrated in the Banjarmasin and Banjarbaru regions.

### B. Validity and Reliability

The measurement model or outer model describes the relationship between latent variables and their indicators. This model serves to measure the validity and reliability of each indicator. Evaluation of the measurement model includes three main steps, namely convergent validity, discriminant validity, and composite reliability tests.

The convergent validity test assesses the ability of indicators to reflect the construct or latent variable being measured. This test is done by checking the outer loadings value. Indicators are considered valid if the outer loadings value is more than 0.70, which indicates that the indicator can explain more than 50% of the variance of the measured construct. This convergent validity test consists of two main components, namely Factor Loading and Average Variance Extracted (AVE). To achieve sufficient convergent validity, the AVE value of each latent variable must be more than 0.5, indicating that the latent construct is able to explain more than half of the variation in its indicators.

The discriminant validity test aims to ensure that a latent variable has a stronger relationship with its indicators than other latent variables. This test is carried out using two methods, namely the Fornell-Larcker Criterion and Cross Loadings. In Cross Loadings, discriminant validity is achieved if the indicator load on the related latent variable is greater than the load on other variables. Meanwhile, the Fornell-Larcker Criterion states discriminant validity when the square root value of the AVE of each variable is greater than the correlation with other variables. In other words, discriminant validity is considered good if the AVE square root of each exogenous construct exceeds the correlation between constructs.

Reliability tests are carried out to determine the consistency of the model, evaluating the extent to which variations in model results are caused by variations in the original data and not by measurement errors, for example from respondents' misunderstanding of questions. Reliability is measured through two main indicators, namely composite reliability and Cronbach's Alpha. If the composite reliability value is more than 0.70, the latent variable is considered to have good reliability. Cronbach's Alpha is also used as a measure of reliability, with a rating scale: 0.81 to 1.00 (highly reliable), 0.61 to 0.80 (reliable), 0.42 to 0.60 (moderately reliable), 0.21 to 0.41 (unreliable), and 0.00 to 0.20 (highly unreliable).

The final results of validity and reliability testing show that there are eighteen (18) indicators that do not meet the critical value, so they are declared invalid. Invalid indicators include DP3 (Platform Quality and Design), MA4 (Mobile Application), OP2 and OP3 (Online Payment), PEOU2 (Perceived Ease of Use), PU2 and PU3 (Perceived Usability), FC4 (Supporting Conditions), PE1 and PE4 (Performance Expectations), TR1 and TR3 (Trust), PB4 (Perceived Benefits), SI2 (Social Influence), IQ2 (Information Quality), SQ3 and SQ4 (Service Quality), and INT2 (Intention to Use IT Services for River Tourism). The final results of outer loading are in Table I and reliability measurements are in Table II.

TABLE I Final Result of Outer Loadings

| Variable | Indicator | Outer Loadings |
|---|---|---|
| Platform Quality and Design (DP) | DP1 | 0,779 |
| | DP2 | 0,778 |
| | DP4 | 0,800 |
| Security (SC) | SC1 | 0,773 |
| | SC2 | 0,753 |
| | SC3 | 0,750 |
| | SC4 | 0,715 |
| Mobile Application (MA) | MA1 | 0,750 |
| | MA2 | 0,745 |

| Variable | Indicator | Outer Loadings |
|---|---|---|
| | MA3 | 0,782 |
| Online Payment (OP) | OP1 | 0,804 |
| | OP4 | 0,854 |
| Perceived Ease of Use (PEOU) | PEOU1 | 0,773 |
| | PEOU3 | 0,812 |
| | PEOU4 | 0,707 |
| Perceived Usefulness (PU) | PU1 | 0,824 |
| | PU4 | 0,840 |
| Facilitating Conditions (FC) | FC1 | 0,812 |
| | FC2 | 0,738 |
| | FC3 | 0,794 |
| Performance Expectancy (EE) | PE2 | 0,838 |
| | PE3 | 0,787 |
| Trust (TR) | TR2 | 0,873 |
| | TR4 | 0,832 |
| Perceived Risk (PR) | PR1 | 0,773 |
| | PR2 | 0,804 |
| | PR3 | 0,762 |
| | PR4 | 0,813 |
| Perceived Benefit (PB) | PB1 | 0,759 |
| | PB2 | 0,753 |
| | PB3 | 0,801 |
| Social Influence (SI) | SI1 | 0,805 |
| | SI3 | 0,775 |
| | SI4 | 0,707 |
| Information Quality (IQ) | IQ1 | 0,819 |
| | IQ3 | 0,783 |
| | IQ4 | 0,741 |
| Service Quality (SQ) | SQ1 | 0,870 |
| | SQ2 | 0,757 |
| Intention to Use IT Services for River Tourism (INT) | INT1 | 0,810 |
| | INT3 | 0,786 |
| | INT4 | 0,759 |

TABLE II REALIBILITY MEASUREMENT RESULTS

| Variable | Composite Reliability | Cronbach's Alpha |
|---|---|---|
| Platform Quality and Design (DP) | 0,829 | 0,690 |
| Security (SC) | 0,836 | 0,738 |
| Mobile Application (MA) | 0,803 | 0,633 |
| Online Payment (OP) | 0,815 | 0,548 |
| Perceived Ease of Use (PEOU) | 0,809 | 0,646 |
| Perceived Usefulness (PU) | 0,818 | 0,555 |
| Facilitating Conditions (FC) | 0,825 | 0,682 |
| Performance Expectancy (PE) | 0,795 | 0,487 |
| Trust (TR) | 0,842 | 0,627 |
| Perceived Risk (PR) | 0,868 | 0,804 |
| Perceived Benefit (PB) | 0,815 | 0,659 |
| Social Influence (SI) | 0,807 | 0,644 |

### *C. Structural Model and Hypothesis Testing*

The inner model, or structural model, is used to assess the predictive ability of the model and the relationship between variables by seeing how well the independent variables can explain the dependent variable in the model. Some of the key criteria in evaluating the structural model include the R-square value and level, as well as the significance of the path coefficients. A high R-square value is required for the main target variable, because the higher the R-square value, the greater the ability of the model to explain variations in the dependent variable. The R-square rating scale is as follows: $\geqslant$ 0.67 is considered good, 0.66 to 0.33 moderate, and 0.32 to 0.19 weak.

In this research model, the Supporting Conditions (FC) variable has an R-square value of 0.361, which indicates that the Mobile Application (MA) and Online Payment (OP) variables together explain 36.1% of the variation in Supporting Conditions (FC), and are categorized as a moderate inner model. The variable Intention to Use River Tourism IT Services (INT) has an R-square value of 0.411, which means that the variables of Perceived Usefulness (PU), Supporting Conditions (FC), Performance Expectations (PE), Trust (TR), Perceived Risk (PR), Perceived Benefits (PB), Social Influence (SI), Information Quality (IQ), and Service Quality (SQ) collectively explain 41.1% of the variation in Intention to Use River Tourism IT Services (INT), and this is also included in the moderate category.

The R-square value for the Perceived Ease of Use (PEOU) variable is 0.270, which indicates that the Platform Quality and Design (DP) variable explains 27% of the variation in Perceived Ease of Use (PEOU), so it is categorized in the weak model. Meanwhile, the R-square value of Perceived Risk (PR) of 0.109 indicates that Security (SC) only explains 10.9% of the variation in Perceived Risk (PR). Since this value is below the minimum limit of 0.190 on the R-square scale, Risk Perception (PR) is categorized as invalid or not explaining enough variation in the model.

Finally, the R-square value for Perceived Usefulness (PU) of 0.288 indicates that Perceived Ease of Use (PEOU) explains 28.8% of the variation in Perceived Usefulness (PU), which is categorized as weak. The complete R-square results can be seen in Table III below.

TABLE III R-SQUARE VALUE

| Variable | R-square | Description |
|---|---|---|
| FC | 0,361 | Moderate |
| INT | 0,411 | Moderate |
| PEOU | 0,270 | Weak |
| PR | 0,109 | Not Enough |
| PU | 0,288 | Weak |

The P-Value calculation is used as the basis for PLS-SEM testing. The bootstrapping method is the most commonly applied technique for estimating standard errors in PLS-SEM. Hypothesis testing is done by considering the Original Sample value, T-Statistic, and P-Value. The conclusion regarding the acceptance or rejection of the hypothesis can be determined based on the T-Statistics value. The critical values commonly used to test the significance of path coefficients are 1.65 (10% significance level), 1.96 (5% significance level), and 2.57 (1% significance level). The choice of significance level depends on the purpose and field of study; generally, a 10% significance

level is assumed in exploratory research, while a 5% level is used in marketing research.

In this study, T-Statistics values greater than 1.96 (5% significance level) indicate that the hypothesis is accepted, while values below 1.96 indicate that the hypothesis is rejected. In addition, the P-Value can also determine the acceptance of the hypothesis; the hypothesis will be accepted if the P-Value is less than 0.05. This study involved 14 variables and 471 respondents, with the error rate set at 5% or 0.050. The results of hypothesis testing using the bootstrapping method in SmartPLS can be seen in Table IV.

TABLE IV RELIABILITY MEASUREMENT RESULTS

| Hypothesis | T-Statistics (\|O/STDEV\|) | P-Value | Description |
|---|---|---|---|
| H1: DP → PEOU | 10.652 | 0.000 | Hypothesis Accepted |
| H2: SC → PR | 5.707 | 0.000 | Hypothesis Accepted |
| H3: MA → FC | 7.979 | 0.000 | Hypothesis Accepted |
| H4: OP → FC | 7.244 | 0.000 | Hypothesis Accepted |
| H5: PEOU → PU | 11.659 | 0.000 | Hypothesis Accepted |
| H6: PU → INT | 1.146 | 0.252 | Hypothesis Rejected |
| H7: FC → INT | 1.926 | 0.054 | Hypothesis Rejected |
| H8: PE → INT | 1.555 | 0.120 | Hypothesis Rejected |
| H9: TR → INT | 1.622 | 0.105 | Hypothesis Rejected |
| H10: PR → INT | 3.392 | 0.001 | Hypothesis Accepted |
| H11: PB → INT | 2.022 | 0.043 | Hypothesis Accepted |
| H12: SI → INT | 4.318 | 0.000 | Hypothesis Accepted |
| H13: IQ → INT | 2.288 | 0.022 | Hypothesis Accepted |
| H14: SQ → INT | 1.196 | 0.232 | Hypothesis Rejected |

### *D. Structural Model and Hypothesis Testing*

Importance-Performance Map Analysis (IPMA) was used to evaluate the factors influencing Intention to Use River Tourism IT Services (INT) with a PLS-SEM approach. IPMA enables a deeper understanding of the PLS-SEM model by assessing alternative path coefficients as measures of importance. In addition, IPMA includes latent constructs as well as the performance of each variable tested. In this study, 14 main factors, namely Platform Quality and Design (DP), Security (SC), Mobile Application (MA), Online Payment (OP), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Supporting Conditions (FC), Performance Expectations (PE), Trust (TR), Perceived Risk (PR), Perceived Benefits (PB), Social Influence (SI), Information Quality (IQ), and Service Quality (SQ), were measured based on their importance and performance. Table V is the result of Importance-Performance Map Analysis as follows.

TABLE V IMPORTANCE-PERFORMANCE MAP ANALYSIS (IPMA)

| Variable | Importance | Performance |
|---|---|---|
| DP | 0.017 | 84.072 |
| SC | -0.038 | 84.781 |
| MA | 0.042 | 84.722 |
| OP | 0.038 | 82.288 |
| PEOU | 0.033 | 83.558 |
| PU | 0.062 | 84.004 |
| FC | 0.112 | 83.055 |
| PE | 0.090 | 84.063 |
| TR | 0.080 | 84.568 |
| PR | -0.114 | 83.567 |
| PB | 0.128 | 83.311 |
| SI | 0.251 | 79.603 |
| IQ | 0.126 | 84.931 |
| SQ | 0.064 | 84.686 |

Based on the IPMA results, the variable with the highest importance is SI, followed by PB, IQ, FC, PE, TR, SQ, PU, MA, OP, PEOU, DP, SC, and PR have the lowest importance. For the highest performance, the variable with the highest value is IQ, followed by SC, MA, SQ, TR, DP, PE, PU, PR, PEOU, PB, FC, OP, and SI are in the lowest order. The IPMA results are visualized in the form of a graph, where the horizontal axis represents the importance value (Total Effects) of the various influencing factors, on a scale of 0 to 1. Meanwhile, the vertical axis shows the performance of these factors on a scale from 0 to 100.

### *E. Artificial Neural Network (ANN) Testing*

Artificial Neural Network (ANN) testing was conducted to strengthen the results of the PLS-SEM analysis and assess the relative importance of the significant factors generated by SEM. The results of SEM analysis showed that all hypothesized relationships were accepted, while ANN was used to validate these results, focusing on variables that were considered important based on PLS-SEM. In this study, variables such as DP, IQ, MA, OP, PEOU, PR, SC, SI, and PB were tested using the ten-fold cross-validation method with one-hidden layer to prevent overfitting. The application used was IBM SPSS Statistics 27.

ANNs produce performance metrics such as Root Mean Squared Error (RMSE), which measures the average error between the actual value and the resultant value of the ANN. The smaller the RMSE value, the better the model performance. In addition, the importance scores generated by the ANN show how much each variable contributes to the output. Sum of Squared Errors (SSE) values close to zero indicate that the model has a smaller random error component, making the model more suitable for use. The smaller the RMSE value, the higher the accuracy of the ANN model using in Fig. 2.

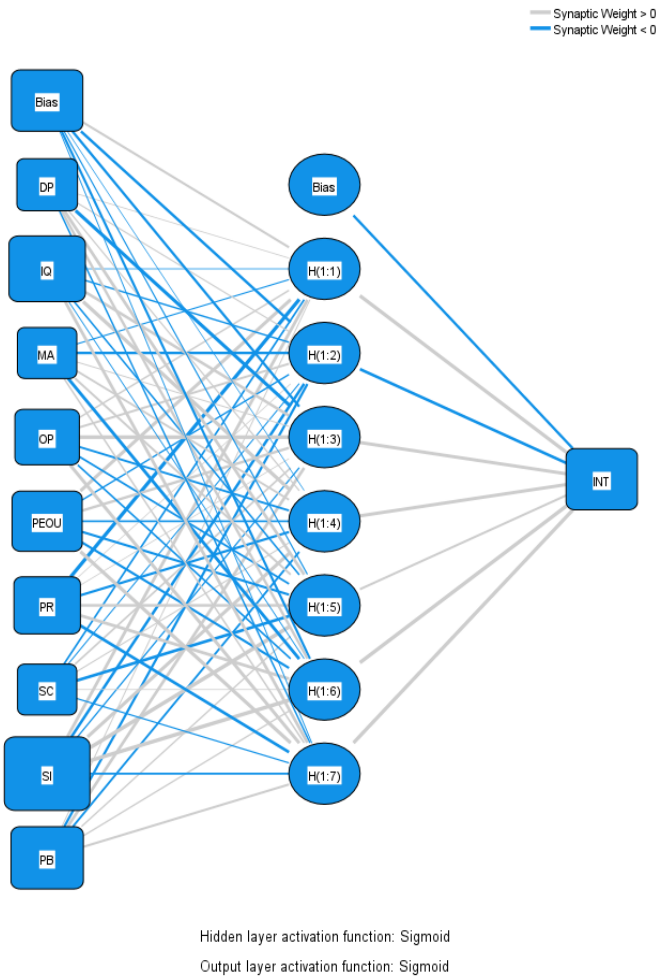


Fig. 2. Artificial neural network (ANN) model.

TABLE VI RMSE VALUE FOR ANN TRAINING AND TESTING

| NN | Training | | | Testing | | | Total Sample N1 + N2 |
|---|---|---|---|---|---|---|---|
| | N1 | SSE | RMSE | N2 | SSE | RMSE | |
| 1 | 383 | 4,076 | 0,103 | 88 | 0,799 | 0,095 | 471 |
| 2 | 367 | 5,236 | 0,119 | 104 | 1,349 | 0,114 | 471 |
| 3 | 389 | 4,057 | 0,102 | 82 | 0,966 | 0,109 | 471 |
| 4 | 375 | 4,154 | 0,105 | 96 | 0,834 | 0,093 | 471 |
| 5 | 369 | 3,924 | 0,103 | 102 | 1,067 | 0,102 | 471 |
| 6 | 384 | 4,089 | 0,103 | 87 | 0,962 | 0,105 | 471 |
| 7 | 357 | 3,919 | 0,105 | 114 | 1,200 | 0,103 | 471 |
| 8 | 385 | 6,191 | 0,127 | 86 | 1,381 | 0,127 | 471 |
| 9 | 371 | 4,021 | 0,104 | 100 | 1,012 | 0,101 | 471 |
| 10 | 369 | 4,221 | 0,107 | 102 | 1,117 | 0,105 | 471 |
| **Average** | | 4,389 | **0,108** | | 1,069 | **0,105** | |
| **Standard Dev.** | | 0,701 | 0,008 | | 0,187 | 0,009 | |

The results from the Artificial Neural Network (ANN) testing in Table VI showed an average RMSE for training (N1) of 0.108 and for testing (N2) of 0.105, with standard deviations of 0.008 and 0.009, respectively. This indicates that the model has a low and consistent error rate, both when training and testing the data. The average SSE value for training was 4.389 and for testing was 1.069, indicating a relatively small amount of squared error. Overall, the ANN model performed well and was stable, with minimal error.

The sensitivity analysis stage was conducted by calculating the importance of each input in the form of a percentage, as shown in Table VII, referred to as the normalized importance. This is obtained by dividing the relative importance value of each input variable by the highest importance value in the ANN model. This process aims to understand how much each variable contributes in influencing the final outcome. This sensitivity analysis also helps to rank the exogenous variables, so that it can be known which ones are the most influential in the model.

TABLE VII SENSITIVITY VALUE

| NN | DP | IQ | MA | OP | PEOU | PR | SC | SI |
|---|---|---|---|---|---|---|---|---|
| 1 | 0,123 | 0,678 | 0,080 | 0,261 | 0,458 | 0,329 | 0,076 | 1,000 |
| 2 | 0,645 | 0,368 | 0,101 | 0,382 | 0,479 | 0,627 | 0,099 | 1,000 |
| 3 | 0,290 | 0,801 | 0,151 | 0,257 | 0,884 | 0,492 | 0,156 | 1,000 |
| 4 | 0,434 | 0,851 | 0,130 | 0,442 | 0,410 | 0,255 | 0,241 | 1,000 |
| 5 | 0,217 | 0,735 | 0,236 | 0,389 | 0,357 | 0,525 | 0,189 | 1,000 |
| 6 | 0,420 | 0,755 | 0,106 | 0,227 | 0,507 | 0,309 | 0,128 | 1,000 |
| 7 | 0,563 | 0,475 | 0,557 | 0,504 | 0,221 | 0,168 | 0,263 | 1,000 |
| 8 | 0,281 | 0,511 | 0,463 | 0,369 | 0,805 | 0,264 | 0,172 | 0,070 |
| 9 | 0,523 | 0,814 | 0,213 | 0,680 | 0,293 | 0,422 | 0,297 | 1,000 |
| 10 | 0,187 | 0,739 | 0,577 | 0,410 | 0,112 | 0,091 | 0,257 | 1,000 |
| **Average Importance** | 0,368 | 0,673 | 0,261 | 0,392 | 0,453 | 0,348 | 0,188 | 0,907 |
| **Normalized Importance** | 41% | 74% | 29% | 43% | 50% | 38% | 21% | 100% |

### F. Discussion of SEM-ANN Results

This study examines the factors that influence the intention to use IT services in river tourism, finding several key findings. Good platform quality and design increase perceived ease of use, making users more comfortable accessing services. Security factors are also significant in reducing perceived risk, indicating the importance of data encryption and strong security systems to increase user trust. Mobile apps play an important role in creating optimal enabling conditions, while secure online payment options support user convenience in digital transactions. While perceived usefulness does not directly affect usage intentions, the benefits of the service must be clearly conveyed to increase interest.

Some factors, such as enabling conditions and performance expectations, were not significant to usage intention. Service providers need to provide realistic information and adequate support to make users feel helpful. User trust, although not significant, should still be built through transparent policies and responsive services. Perceived risk has a negative effect on intention to use, so risk mitigation strategies are important to reduce user concerns. Perceived benefits and social influence proved to be the dominant factors driving usage intention, where recommendations from close people and clear and relevant information can increase interest. Although service quality is not significant, providers should focus on delivering compelling benefits and information to make users more interested in switching to these IT services.

This study tested SEM-based IPMA and ANN-based sensitivity analysis with the results showing that Social Influence (SI), Perceived Benefits (PB), and Information Quality (IQ) are the three most significant independent variables in influencing user intentions. SI has the highest importance value in both methods, 0.251 in IPMA and 0.907 in ANN, indicating that this factor is very important in influencing user decisions, although its performance still needs to be improved. PB, with a value of 0.128 in IPMA and 0.730 in ANN, indicates that users' perceived benefits are also quite influential on their intentions. IQ, with a value of 0.126 in IPMA and 0.673 in ANN, indicates that the quality of information provided by the platform is very important to users. Based on result comparison shown in Table VIII, it shows that the alignment between the two analyses and reinforce the importance of these three variables in driving user intentions.

TABLE VIII COMPARISON OF IMPORTANCE VALUES FOR VARIABLES IN IPMA AND SENSITIVITY ANALYSIS

| Variable | IPMA Importance | Sensitivity Analysis Importance |
|---|---|---|
| SI | 0.251 | 0,907 |
| PB | 0.128 | 0,730 |
| IQ | 0.126 | 0,673 |

## V. CONCLUSION

This research aims to analyze the factors that influence the acceptance and utilization of information technology in river tourism services in South Kalimantan. The method used is a Hybrid SEM-ANN approach on 471 respondents, which provides an in-depth understanding of the interaction between relevant variables. The results show three main factors that have a significant effect on user intention to use the service, namely Social Influence, Perceived Benefits, and Information Quality. Social Influence has the strongest impact on driving user intentions, followed by Perceived Benefits that strengthen intentions by providing direct benefits from using the service, and Information Quality that provides clarity and certainty in decision-making.

Based on these findings, the study recommends several strategies to increase the adoption of information technology-[22] based river tourism services. Strengthening Social Influence can be done by utilizing social media or digital platforms, through campaigns involving user testimonials, interactions between users, and loyalty programs. Increasing Perceived Benefits can be achieved by adding value-added features, such as service personalization, up-to-date information on routes and river conditions, and easy access to assistance services. On the other hand, Information Quality needs to be maintained by ensuring all information is regularly updated, easy to understand, and accurate, especially regarding river tourism facilities and conditions.

However, this study is not without limitations. First, the data were collected only from users in South Kalimantan, which may limit the generalizability of the findings to other regions or tourism contexts. Second, the model focuses on selected variables, which, although significant, may not capture other potential factors influencing technology adoption in river tourism. Lastly, the cross-sectional nature of the data limits the ability to observe changes in user behavior over time. Future research could address these limitations by expanding the geographical scope, incorporating additional variables, and using longitudinal designs.

The results of this study are expected to serve as a guide for managers and stakeholders in designing IT services that are more effective and in line with user needs, while also encouraging further investigation into broader factors and contexts affecting technology adoption in tourism.

## ACKNOWLEDGMENT

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# Mitigating Catastrophic Forgetting in Continual Learning Using the Gradient-Based Approach: A Literature Review

Haitham Ghallab, Mona Nasr, Hanan Fahmy
Department of Information Systems-Faculty of Computers and Artificial Intelligence, Helwan University, Cairo, Egypt

***Abstract*—Continual learning, also referred to as lifelong learning, has emerged as a significant advancement for model adaptation and generalization in deep learning with the capability to train models sequentially from a continuous stream of data across multiple tasks while retaining previously acquired knowledge. Continual learning is used to build powerful deep learning models that can efficiently adapt to dynamic environments and fast-shifting preferences by utilizing computational and memory resources, and it can ensure scalability by acquiring new skills over time. Continual learning enables models to train incrementally from an ongoing stream of data by learning new data as it comes while saving old experiences, which eliminates the need to collect new data with old data to be retrained together from scratch, saving time, resources, and effort. However, despite continual learning advantages, it still faces a significant challenge known as catastrophic forgetting. Catastrophic forgetting is a phenomenon in continual learning where a model forgets previously learned knowledge when trained on new tasks, making it challenging to preserve performance on earlier tasks while learning new ones. Catastrophic forgetting is a central challenge in advancing the field of continual learning as it undermines the main goal of continual learning, which is to maintain long-term performance across all encountered tasks. Therefore, several types of research have been proposed recently to address and mitigate the catastrophic forgetting dilemma to unlock the full potential of continual learning. As a result, this research provides a detailed and comprehensive review of one of the state-of-the-art approaches to mitigate catastrophic forgetting in continual learning known as the gradient-based approach. Furthermore, a performance evaluation is conducted for the recent gradient-based models, including the limitations and the promising directions for future research.**

***Keywords*—Deep learning; continual learning; model adaptation and generalization; catastrophic forgetting; gradient-based approach***

## I. Introduction and Problem Definition

Human beings and other species possess the innate ability to learn, adapt, and retain information throughout their existence. This natural capability, termed continuous learning, is supported by neurocognitive mechanisms that enable organisms to dynamically adapt to new experiences while retaining prior knowledge. Neurocognitive mechanisms involve a complex interplay of neurons and synapses that dynamically process, store, and retrieve information. The brain achieves this remarkable feat through processes such as neuroplasticity, which allows neural pathways to adapt in response to new experiences, and consolidation, which stabilizes memories and integrates them with prior knowledge. This enables humans and animals to continuously acquire, refine, and transfer knowledge while retaining previous learning [1]. For example, humans can learn new skills, such as playing a musical instrument, without losing the ability to perform unrelated tasks like speaking or walking. And since deep learning mimics certain aspects of the human brain, particularly how neurons in the brain process and transmit information, then deep learning can use this biological efficiency to incrementally train its models, but unfortunately unlike the human neurocognitive mechanisms, mimicking continual learning in artificial neural networks contrasts sharply with the challenges referred to as catastrophic forgetting—a phenomenon where the acquisition of new knowledge disrupts or erases previously learned information. Addressing this limitation is central to advancing continual learning systems in artificial intelligence [2].

Continual learning, also known as lifelong learning, seeks to emulate the brain's neurocognitive mechanisms in artificial systems. By enabling models to incrementally learn and adapt to new information without forgetting past knowledge, continual learning systems aim to achieve human-like adaptability. These systems have far-reaching implications for applications in dynamic environments, such as robotics, autonomous vehicles, financial forecasting, environmental monitoring, adaptive user interface, and personalized healthcare, where consistent performance across evolving tasks is essential [2], [3]. Deep learning has revolutionized the interaction with technology and process data. By mimicking the way the human brain works, it enables systems to learn from experience, adapt to new information, and perform tasks without explicit programming. This makes deep learning crucial in automating complex processes, improving accuracy, and handling vast amounts of data, which are essential in today's data-driven world.

Before continual learning and other common model adaptation and generalization paradigms, deep learning models used to be trained using fixed datasets, which caused a major challenge especially in dynamic real-time environments where new data arrives continuously and data distribution shifts sharply therefore deep learning models struggled to maintain accuracy.

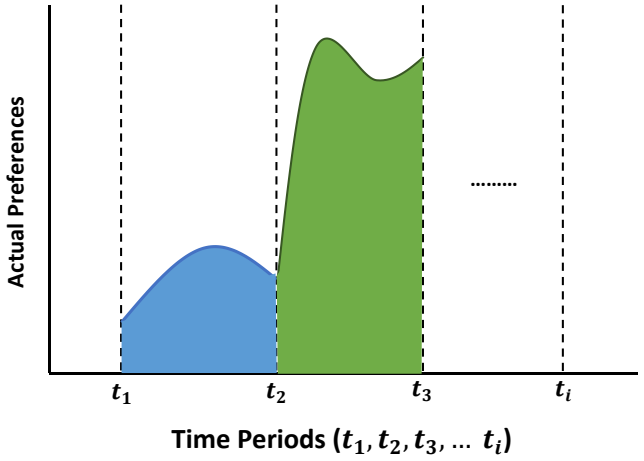


Fig. 1. Data distribution shifts in dynamic environments.

Additionally, deep learning models require significant computational power and large-scale datasets to function effectively, especially for training, as these models often need specialized hardware like GPUs and large amounts of labeled data to produce accurate results [4], which is a challenge especially when building models for real-time multi-task classification purposes in dynamic environments. This is a key problem in deep learning and real-time analysis, where data preferences and patterns are changed rapidly over time as shown in Fig. 1. In this case, traditional deep learning models often use an iterative deployment mechanism to keep up with the changing patterns by collecting the new arriving stream of data with old experiences and training the model from scratch to include the entire set of data and not lose efficiency, and this solution is computationally expensive and inefficient.

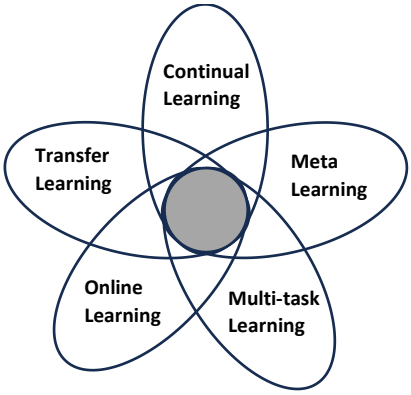


Fig. 2. Model adaptation and generalization paradigms.

As a result, several model adaptation and generalization paradigms have been proposed to address this challenge either by incrementally training deep learning models with new experiences as in continual learning (also referred to as incremental learning, lifelong learning, continuous learning) [5], or by allowing models to adapt to new unseen tasks by utilizing related past experiences using multi-task learning, meta-learning, transfer learning, or online learning [5], [6], [7], [8], [9]. As shown in Fig. 2, although the objectives of these learning paradigms may differ, they may overlap in certain aspects, which sometimes may confuse the researchers. Table I shows the main differences and highlights the focus of each approach.

Although, continual learning shows a significant contribution to deep learning, especially in dynamic environments by enabling models to adapt efficiently and maintain accuracy to data distribution shifts and multi-task processes, with minimum and constant computation powers and memory utilization. But continual learning still faces a significant challenge known as catastrophic forgetting [2], [5]. Catastrophic forgetting, also referred to as catastrophic interference, is a phenomenon in continual learning where a model forgets previously learned knowledge when trained on new tasks, making it challenging to preserve performance on earlier tasks while learning new ones. Catastrophic forgetting is a central challenge in advancing the field of continual learning as it undermines the main goal of continual learning, which is to maintain long-term performance across all encountered tasks [2], [5]. However, it is important to highlight that while some model adaptation and generalization paradigms, such as multi-task learning and transfer learning, improve learning efficiency and generalization across tasks, they do not directly address the issue of catastrophic forgetting [6],[9]. Unlike continual learning, which is specifically designed to retain previously learned knowledge while learning new tasks sequentially [5].

TABLE I MODEL ADAPTATION AND GENERALIZATION PARADIGMS

| Learning Paradigm | Main Objective |
|---|---|
| Continual Learning [5] | Enable models to learn from a continuous stream of tasks without forgetting previously learned knowledge, which is very significant in dynamic environments with high data distribution shits over time. |
| Multi-task Learning [6] | Enable models to solve multiple related tasks simultaneously. Instead of treating each task independently, models leverage shared information across similar tasks to improve the learning efficiency and generalization performance of all tasks. |
| Meta Learning [7] | Enable models to perform effectively in rare unseen tasks where datasets are currently evolving and not yet available, by utilizing similar experiences from related tasks. It requires diverse task datasets for meta-training, and few-shot or limited data for testing/adaptation. |
| Online Learning [8] | Enable models to immediate and real-time short-term adaptation to the recent observations and does not inherently address long-term retention of knowledge or ensure that past patterns are preserved, for instance online learning models might update their predictions as new data arrives without revisiting historical data. |
| Transfer Learning [9] | Enable models to reuse knowledge learned from a source task or domain to improve learning on a target task or domain. Instead of training a model from scratch for every task. It involves pretraining on a large source dataset and fine-tuning on the target task. |

So, the primary objective of this research is to address the main issues of catastrophic forgetting in continual deep learning and recent potential solutions. Section II introduces the background and key concepts underlying continual deep learning, establishing a foundational understanding of the topic. Section III presents an overview of the latest gradient-based approaches developed to mitigate catastrophic forgetting in continual deep learning. Finally, Section IV offers a

discussion of the research and Section V presents conclusions, limitations, and directions for future work.

## II. Background and Key Concepts

The field of continual learning addresses one of the most significant challenges in artificial intelligence: enabling systems to learn sequentially from non-stationary data while retaining previously acquired knowledge. Unlike traditional deep learning without adaptation and generalization capabilities, where models are trained on static datasets, continual learning operates in dynamic environments where new tasks or patterns continuously emerge. However, this learning paradigm faces two fundamental challenges:

*a) Catastrophic forgetting*: The tendency of neural networks to lose performance on previously learned tasks when trained on new ones [10].

*b) Stability-plasticity dilemma*: The need to balance the retention of old knowledge (stability) with the incorporation of new information (plasticity) [11].

These challenges have profound implications for real-world applications, including robotics, autonomous systems, and personalized assistants, where adaptability and knowledge retention are paramount. Below, the research explained the key concepts underpinning continual learning in deep learning tasks, and its associated challenges to establish a foundational understanding of the topic.

### A. Continual Learning

Continual Learning, also known as lifelong learning, is one of the most common model adaptation and generalization paradigms, as it refers to the ability of a deep learning model to learn from a continuous stream of tasks without forgetting previously learned knowledge [5], [12]. Unlike traditional deep learning setups, where models are trained on a fixed dataset, continual learning simulates a dynamic learning environment where new tasks emerge sequentially. For instance, continual learning aims to train models on a sequence of $N$ tasks $T_1, T_2, T_3, \ldots, T_N$, where each task $T_i$ is defined by its dataset $D_i = \{(x_j, y_j)\}_{j=1}^{n_i}$ and its objective $L_i(\theta)$, with θ denoting the model parameters, and the purpose of the model is to minimize the cumulative loss across all tasks, as shown in Eq. (1).

$$\theta^* = arg \min_{\theta} \sum_{i=1}^{N} L_i(\theta) \qquad (1)$$

So, the continual learning model main objective is to perform this optimization without degrading performance on earlier tasks, $T_1, T_2, T_3, \ldots, T_{i-1}$ when learning task $T_i$, but this is challenging because the datasets $D_i$ are typically not accessible once the task $T_i$ is completed, and therefore continual learning model making it hard to preserve performance on earlier tasks while learning new ones and respectively mitigating the famous problem of continual deep learning known as the catastrophic forgetting dilemma [10], as shown in Fig. 3.

For example, Fig. 3 shows the performance of a baseline model and a continual learning model across sequential tasks $T_1, T_2, T_3, \ldots, T_{i-1}$. The baseline model suffers a sharp decline in earlier task performance (catastrophic forgetting), while the continual learning model maintains better stability. Furthermore, continual learning must navigate the delicate balance between maintaining model stability—preserving knowledge from earlier tasks and ensuring sufficient plasticity to adapt and learn new information as it becomes available, which is another challenge in continual learning known as the stability-plasticity dilemma.

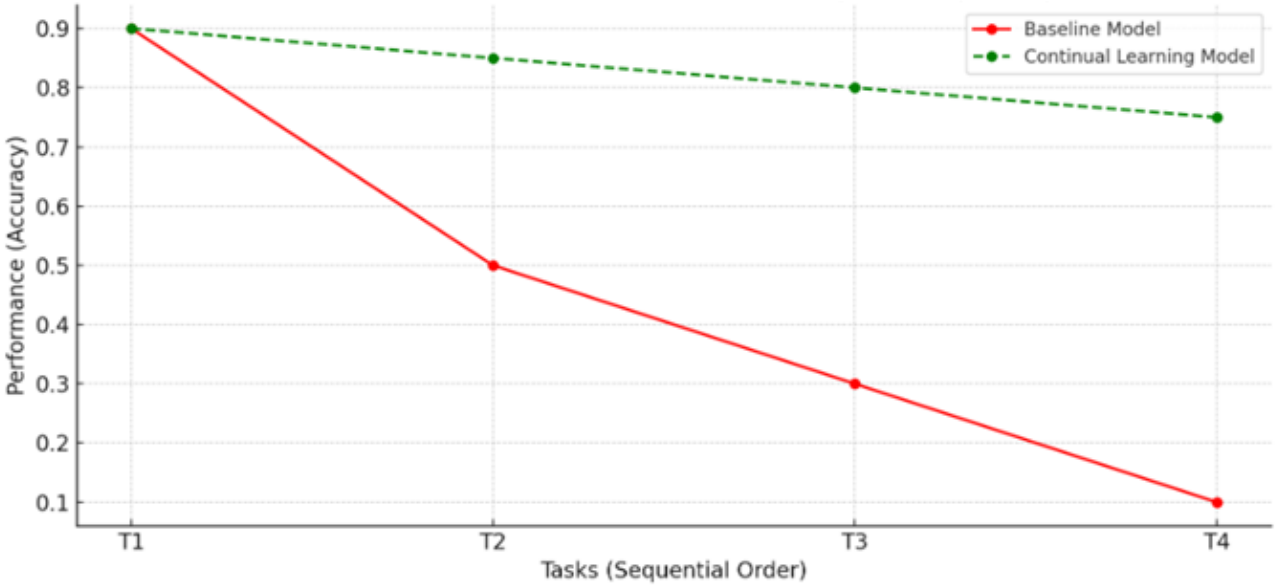


Fig. 3. Task performance over time (Catastrophic forgetting).

### B. Catastrophic Forgetting

Catastrophic forgetting is a main challenge in building continual deep learning models. It refers to the drastic decline in a neural network's performance on previously learned tasks when it is trained on new tasks [2], [10]. This phenomenon occurs because deep learning models typically share a common set of parameters θ across all tasks. When trained on a new task $T_{i+1}$, the optimization process updates θ to minimize the loss for the new task, inadvertently overwriting information critical to earlier tasks. For instance, consider a model trained sequentially on two tasks:

*1) Task 1 ($T_1$):* Loss function $L_1(\theta)$ with dataset $D_1 = \{(x_1, y_1)\}$

*2) Task 2 ($T_2$):* Loss function $L_2(\theta)$ with dataset $D_2 = \{(x_2, y_2)\}$

During training on $T_1$, the model learns parameters $\theta^*$ by minimizing $L_1(\theta)$, as shown in Eq. (2).

$$\theta_{T1}^* = arg \min_{\theta} L_1(\theta) \quad (2)$$

When training begins on $T_2$, the model minimizes $L_2(\theta)$, as shown in Eq. (3).

$$\theta_{T2}^* = arg \min_{\theta} L_2(\theta) \quad (3)$$

However, the gradients $\nabla L_2(\theta)$ used to optimize $T_2$ often conflict with $\nabla L_1(\theta)$. This results in updates to θ that degrade the performance on $T_1$, i.e., $L_1(\theta_{T_2}^*) > L_1(\theta_{T_1}^*)$. As a result, catastrophic forgetting become a central challenge in advancing the field of continual learning in deep learning tasks as it undermines the main goal of continual learning, which is to maintain long-term performance across all encountered tasks. Therefore, the next section will address several types of research that have been proposed recently to address and mitigate the catastrophic forgetting dilemma to unlock the full potential of continual deep learning [2], [10].

### C. Stability-Plasticity Dilemma

The stability-plasticity dilemma is a core challenge in continual deep learning. It refers to the trade-off between:

*1) Stability*: The ability of a model to retain and preserve knowledge from previously learned tasks [11].

*2) Plasticity*: The ability of a model to adapt to new tasks and incorporate new knowledge effectively [11].

In continual deep learning, achieving a balance between these two opposing forces is critical. Excessive stability can lead to rigidity, where the model fails to adapt to new tasks. On the other hand, excessive plasticity can cause catastrophic forgetting, where new learning overwrites previously acquired knowledge [13]. For instance, consider a sequence of *N* tasks $T_1, T_2, T_3, \ldots, T_N$, where each task $T_i$ has its dataset $D_i$ and loss function $L_i(\theta)$, with θ denoting the shared model parameters. The objective in continual learning is to minimize cumulative loss, as shown in Eq. (4).

$$L(\theta) = \sum_{i=1}^{N} L_i(\theta) \quad (4)$$

To address the stability-plasticity dilemma, the following constraints are defined:

*3) Stability constraint:* For previously learned tasks $T_j (j < i)$, the loss should not increase beyond a threshold $\epsilon$, as shown in Eq. (5).

$$L_j(\theta) \leq L_j\left(\theta_{T_j}^*\right) + \epsilon \quad (5)$$

where, $\theta_{T_j}^*$ is the parameter configuration after training on task $T_j$.

*4) Plasticity constraint:* The model must minimize the loss for the current task $T_i$, as shown in Eq. (6).

$$\theta = arg \min_{\theta} L_i(\theta) \quad (6)$$

where, the gradient updates for θ often result in interference between tasks. If the gradients for $T_i$ conflict with $T_j$, the performance on earlier tasks degrades.

As a result, maintaining a balance between these two forces (stability and plasticity) ensures that the model's parameter space retains important information for older tasks, typically through regularization or rehearsal, and it also enable the model to adapt to new tasks and incorporate new knowledge effectively [11], [13].

## III. Mitigating Catastrophic Forgetting Approaches

As mentioned above, continual learning in deep neural networks faces two intertwined challenges: maintaining a balance between stability and plasticity and addressing catastrophic forgetting. Several approaches have been proposed to tackle these two challenges as shown in Fig. 4 categorized broadly into regularization-based, knowledge-distillation-based, Bayesian-based, gradient-based, architecture-based, replay-based, and other hybrid methods.

In this research, the main objective is to focus on the gradient-based approach including its definition, strengths, weakness points, and its recent models including Gradient Episodic Memory (GEM) [14], Averaged Gradient Episodic Memory (A-GEM) [15] and Orthogonal Gradient Descent (OGD) [16]. Additionally, the research presents how the gradient-based approach differs from the other approaches based on factors such as the core idea, memory requirements, computational efficiency, and flexibility.

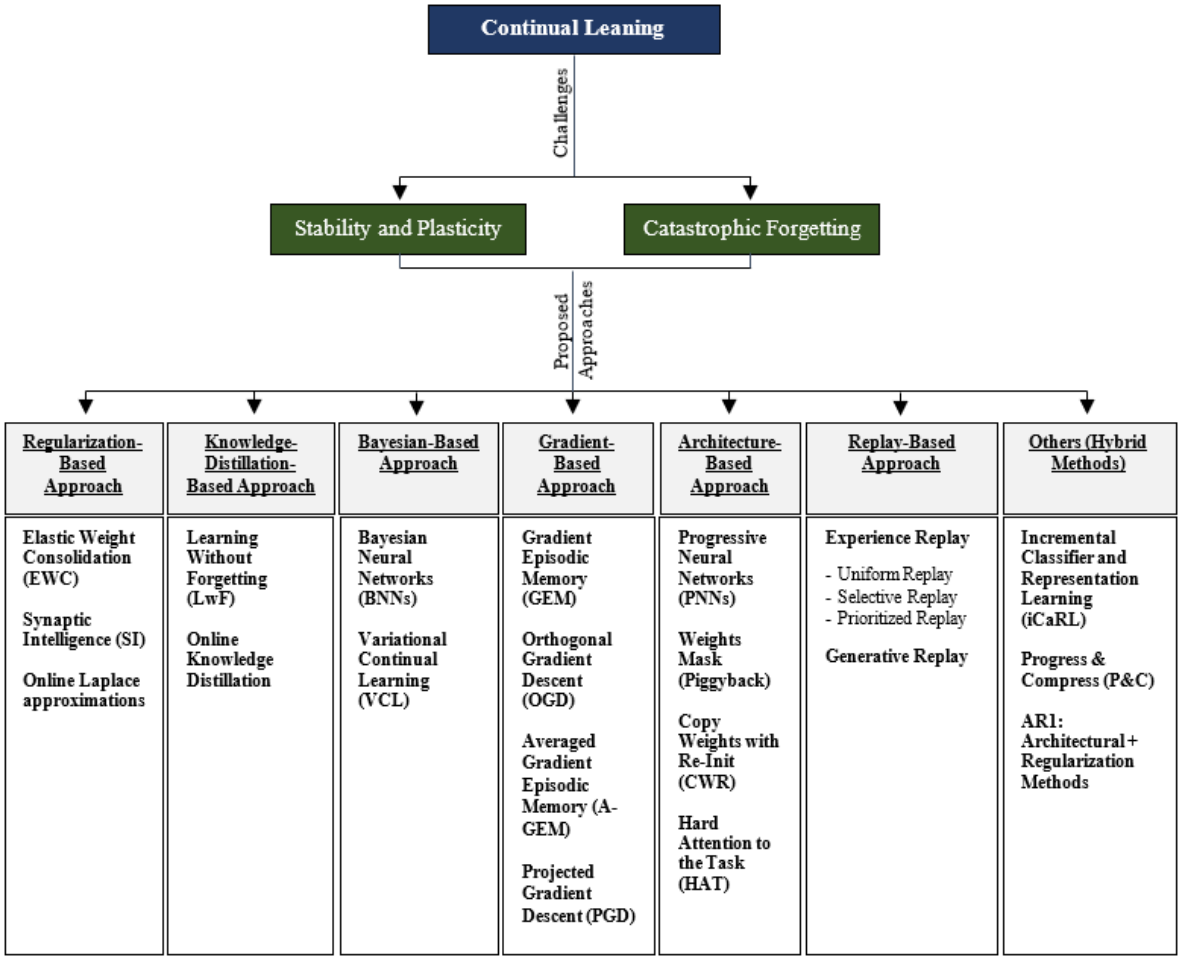


Fig. 4. Mitigating catastrophic forgetting approaches taxonomy.

### A. Gradient-Based Approach

The gradient-based approach is a prominent methodology in continual deep learning, designed to address the challenge of catastrophic forgetting by carefully adjusting the gradient updates when a model learns new tasks. The key idea is to modify the gradient direction to minimize interference with previously learned tasks, ensuring a balance between retaining old knowledge and learning new information [14]. This approach operates within the optimization process, ensuring that parameter updates for new tasks do not disrupt the knowledge gained from previous ones. By focusing on the dynamics of gradients during training, it provides a flexible and efficient framework for tackling forgetting without relying on extensive memory storage or architectural changes. For instance, if a neural network first trained on Task A, where the goal is to classify points into two categories (e.g. red and blue) based on their positions in a 2D plane. After mastering Task A, the network is asked to learn Task B, which involves classifying points into two different categories (e.g. green and yellow) based on a new data distribution. Without careful control, when the network learns Task B, the gradients calculated for this task might overwrite what was learned for Task A, causing catastrophic forgetting. Gradient-based approaches solve this by modifying how the network updates its parameters. Let's illustrate this with Gradient Episodic Memory (GEM):

*1) Memory of task A*: GEM keeps a small memory buffer of examples from Task A (e.g. a few red and blue points). These points represent the knowledge of Task A that the model should not forget.

*2) Gradient check*: When the model computes the gradient to learn Task B, GEM checks if this gradient would increase the loss on the stored Task A examples. If it does, GEM modifies the gradient to ensure that the loss on Task A examples does not worsen.

*3) Adjusted gradient update*: The model updates its parameters using the adjusted gradient, which balances learning for Task B while preserving performance on Task A.

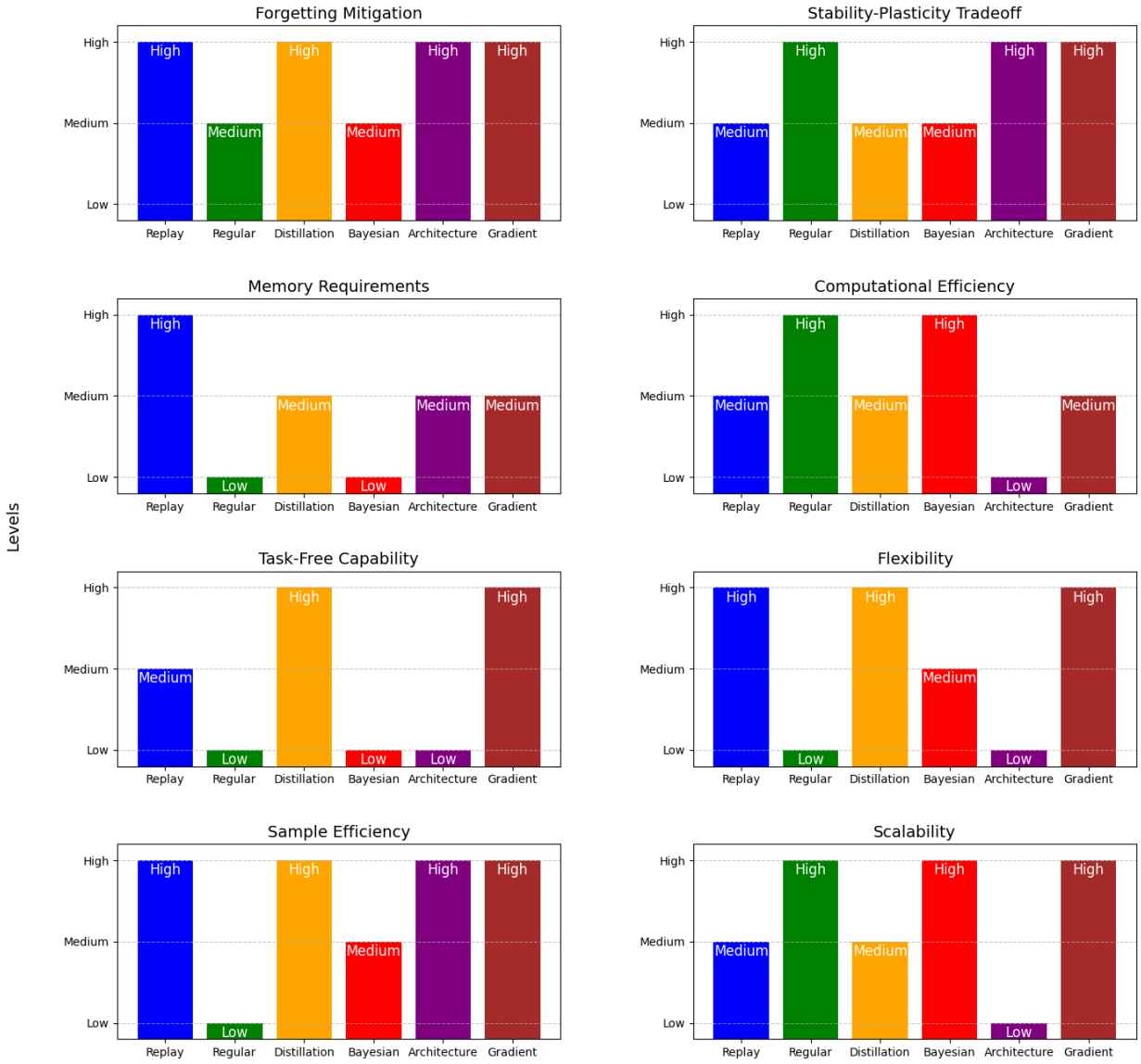


Fig. 5. Key factors for comparing continual learning approaches.

After learning Task A, the optimal parameter region for Task A is identified (a "safe zone" in the parameter space). When learning Task B, the new gradient points toward the optimal parameters for Task B. However, if this update would move the parameters out of the "safe zone" for Task A, GEM adjusts the gradient direction to stay within a region that satisfies both tasks [14]. This adjustment can be mathematically represented as a projection, as shown in Eq. (7).

$$g_{adjusted} = g - \frac{g^{\top} m}{m^{\top} m} m \qquad (7)$$

where, $g$ is the gradient for Task B, $m$ is the gradient from memory examples of Task A. And finally, $g_{adjusted}$ is the new gradient that minimizes interference with Task A. Think of it like walking a path (Task B) while staying within a marked boundary (Task A). Instead of walking straight ahead (ignoring the boundary), GEM adjusts your step to ensure you remain within the boundary while moving forward. By modifying the gradient updates this way, the model learns Task B without significantly forgetting Task A, achieving a balance between stability (retaining old knowledge) and plasticity (learning new knowledge). Gradient Episodic Memory (GEM) is a key example of this approach. It adjusts gradients during training to ensure that the loss on stored samples from previous tasks does not increase, preserving past knowledge [14]. Averaged Gradient Episodic Memory (A-GEM) simplifies GEM by using averaged gradients across stored samples, reducing computational overhead while maintaining performance [15]. Orthogonal Gradient Descent (OGD) further refines this by projecting the gradients of new tasks onto spaces orthogonal to gradients of old tasks, minimizing interference [16].

Furthermore, to better understand the position of gradient-based methods, it is essential to compare them with other approaches, including replay-based [17], regularization-based [18], knowledge-distillation-based [19], Bayesian-based [20], architecture-based [21], and hybrid methods [22], across

multiple factors as shown in Fig. 5. One of the most important factors is catastrophic forgetting mitigation, which measures how well an approach retains previously learned knowledge while integrating new information. Replay-based, knowledge-distillation-based, and gradient-based methods are particularly effective in this aspect. Another critical factor is the stability-plasticity tradeoff, which reflects an approach's ability to balance learning new tasks while preserving old ones. Regularization-based and architecture-based methods focus more on stability, while gradient-based and replay-based methods offer a better balance between stability and plasticity. Memory requirements vary significantly among continual learning approaches. Replay-based methods require high memory usage since they store past examples, whereas regularization-based and Bayesian-based methods demand far less memory. Gradient-based approaches generally have moderate memory requirements. Similarly, computational efficiency plays a crucial role, as some methods require extensive processing power.

Regularization-based and Bayesian-based approaches are generally efficient, while replay-based and architecture-based methods tend to have higher computational costs due to data storage or network expansion. Another important consideration is task-free capability, which determines whether a method can learn continuously without predefined task boundaries. Knowledge-distillation-based and gradient-based approaches perform well in this aspect, while regularization-based and Bayesian-based approaches typically struggle with task-free learning. Closely related is flexibility, which measures how well an approach adapts to different continual learning settings, such as class-incremental or domain-incremental learning. Replay-based, knowledge-distillation-based, and gradient-based approaches are highly flexible, whereas regularization-based and architecture-based approaches tend to be more constrained. Sample efficiency is another key factor that determines how well a method can learn from a limited number of training examples. Replay-based and gradient-based methods perform well in this regard, as they either revisit stored data or adjust learning strategies dynamically. Finally, scalability is crucial for applying continual learning to large datasets and real-world applications. Regularization-based, Bayesian-based, and gradient-based methods tend to scale better, whereas architecture-based methods struggle due to high computational costs and network expansion constraints. Each of these factors plays a crucial role in determining the best continual learning approach for a given application. Some methods excel in retaining past knowledge, while others prioritize efficiency or adaptability. The ideal approach often depends on the specific constraints of the task, whether it requires high memory efficiency, task-free learning, or the ability to scale to large datasets.

### *B. Gradient Episodic Memory (GEM)*

Gradient Episodic Memory (GEM) is a continual learning model designed to mitigate catastrophic forgetting. Its core component is an episodic memory $M_t$, which retains a subset of previously encountered examples from task t. For ease of implementation, integer task descriptors are used to index the episodic memory. Since integer task descriptors do not inherently support strong forward transfer (i.e., zero-shot learning), GEM instead prioritizes minimizing negative backward transfer by efficiently utilizing memory storage. In practice, the learner has a fixed memory capacity of $M$. If the total number of tasks $T$, is known in advance, memory can be evenly distributed across tasks, allocating $m = M/T$ slots per task. However, if $T$ is unknown, $m$ can be gradually reduced as new tasks are introduced. A simple strategy for memory management involves storing the most recent $m$ examples from each task, though more sophisticated techniques, such as constructing a coreset per task, could improve efficiency [14]. The model parameters denoted as $\theta \in R^p$, define the predictor $f_\theta$, and the loss function is evaluated on the stored examples from task $k$, as shown in Eq. (8).

$$L(f_\theta, M_k) = \frac{1}{|M_k|} \sum_{(x_i,k,y_i)\in M_k} L(f_\theta(x_i, k), y_i) \quad (8)$$

The performance of the Gradient Episodic Memory (GEM) model is evaluated using three benchmark datasets (MNIST Permutations, MNIST Rotations, and Incremental CIFAR100), and the results highlight GEM's strong performance compared to state-of-the-art methods. However, there are three key areas for potential improvement. First, GEM does not utilize structured task descriptors, which could facilitate positive forward transfer and enable zero-shot learning. Second, advanced memory management strategies, such as constructing task-specific coresets, were not explored in this study. Third, GEM requires a separate backward pass for each task during training, leading to increased computational overhead. Addressing these limitations presents promising research opportunities for extending learning models [14].

### *C. Averaged Gradient Episodic Memory (A-GEM)*

Although GEM demonstrates strong effectiveness in a single epoch setting, its performance improvements come at the cost of significant computational overhead during training. At each update step, GEM constructs the matrix $G$ using all stored samples from the episodic memory, making the inner loop optimization computationally expensive, particularly when the memory size $M$ and the number of tasks increase. To address this efficiency challenge, a more computationally feasible variant of GEM, known as Averaged GEM (A-GEM) is introduced [15]. Unlike GEM, which ensures that the loss for each previous task—approximated using episodic memory samples—does not increase at each training step, A-GEM instead seeks to maintain a non-increasing average episodic memory loss across all prior tasks. The objective of A-GEM is shown in Eq. (9).

$$minimize_\theta\ l(f_\theta, D_t)\ \ s.t\ \ l(f_\theta, M) \le l(f_\theta^{t-1}, M) \quad (9)$$

The performance of the Averaged Gradient Episodic Memory (A-GEM) model is evaluated using four datasets stream (MNIST Permutations, CUB Split, AWA Split, and CIFAR). The experimental results shows that A-GEM offers the best balance between final average accuracy and computational/memory efficiency. It is approximately 100 times faster and requires 10 times less memory than GEM while outperforming regularization-based approaches in accuracy. Additionally, leveraging compositional task descriptors enhances few-shot learning across all methods, with A-GEM often achieving the best results. However,

experiments reveal a notable performance gap between lifelong learning (LLL) methods, including A-GEM, trained sequentially and the same model trained in a non-sequential multi-task setting, despite exposure to the same data. While task descriptors improve few-shot learning, the limited cross-task transferability among methods suggests that eliminating forgetting alone is insufficient for effective knowledge transfer. Future research will focus on addressing these challenges [15].

### *D. Orthogonal Gradient Descent (OGD)*

Catastrophic forgetting occurs in neural networks when gradient updates for a new task modify the model without preserving knowledge from previous tasks. To address this issue, the Orthogonal Gradient Descent (OGD) method is introduced, which adjusts the update direction to retain crucial information from earlier tasks. The key principle of OGD, as illustrated in Fig. 4, is to constrain parameter updates to remain within the orthogonal subspace of past task gradients, thereby mitigating interference and preserving learned representations [16].

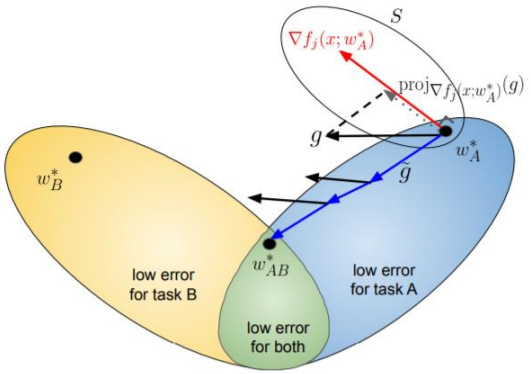


Fig. 6. The Key principle of OGD [16].

An illustration in Fig. 6 demonstrates how Orthogonal Gradient Descent (OGD) adjusts gradient directions to prevent interference between tasks. Here, $g$ represents the original gradient computed for task $B$, while $\tilde{g}$ is its projection onto the orthogonal subspace relative to the gradient $\nabla f_j(x;\ w_A^*)$ from task $A$. Constraining updates within this orthogonal subspace (depicted in blue) enables the model parameters to move toward a region of lower error (shown in green) that benefits both tasks [16].

### *E. Recent Models*

As shown in Table II, several types of research have been proposed to improve performance in overcoming and mitigating catastrophic forgetting in continual deep learning using a gradient-based approach.

Utility-based Perturbed Gradient Descent (UPGD), introduced by Elsayed et al. (2023), is an online learning algorithm designed for continual learning agents. It mitigates forgetting by preserving important weights and features while selectively perturbing less critical ones based on their utility. Empirical results demonstrate that UPGD effectively reduces forgetting and maintains network plasticity, allowing modern representation learning techniques to function efficiently in a continual learning setting. This novel approach enables learning agents to operate over extended periods by implementing utility-aware update rules that safeguard essential parameters while adjusting less significant ones. These rules help address key challenges in continual learning, such as catastrophic forgetting and declining plasticity. Experimental evaluations confirm that UPGD enhances network adaptability and facilitates the reuse of previously learned features, making it particularly suited for environments requiring rapid adaptation to evolving tasks [23].

Adversarial Augmentation with Gradient Episodic Memory (Adv-GEM), showed by Wu et al. (2024), enhances data diversity by leveraging gradient episodic memory. This method strengthens existing continual reinforcement learning (RL) algorithms, improving their average performance, reducing catastrophic forgetting, and facilitating forward transfer in robot control tasks. The framework is designed for easy expansion, allowing for further enhancements. Future research will aim to optimize augmentation efficiency, validate the approach across various real-world scenarios, and develop adaptive strategies to handle different task complexities effectively [24].

Asymmetric Gradient Distance (AGD) metric and Maximum Discrepancy Optimization (MaxDO) strategy, proposed by Lyu et al. (2023), are used in Parallel Continual Learning (PCL) effectively to reduce training conflicts and suppresses forgetting of completed tasks. PCL involves training multiple tasks simultaneously with unpredictable start and end times, leading to challenges such as training conflicts and catastrophic forgetting. These issues arise due to discrepancies in the direction and magnitude of gradients from different tasks. To address this, PCL is formulated as a minimum distance optimization problem among gradients, and an Asymmetric Gradient Distance (AGD) metric is introduced to measure gradient discrepancies. AGD accounts for both gradient magnitudes and directions while allowing a tolerance for minor conflicting gradients, thereby mitigating imbalances in parallel training. Additionally, a Maximum Discrepancy Optimization (MaxDO) strategy is proposed to minimize the largest gradient discrepancy across tasks. Extensive experiments on three image recognition datasets demonstrate the effectiveness of this approach in both task-incremental and class-incremental PCL settings [25].

Unified Gradient Projection with Flatter Sharpness for Continual Learning (UniGrad-FS), proposed by Li et al. (2024), enhances CL performance. The core idea is to apply efficient gradient projection in regions with minimal gradient conflicts, making the method widely compatible with gradient-based optimizers. For evaluation, UniGrad and UniGrad-FS are integrated into two state-of-the-art baselines, WA and MEMO, leading to performance improvements of +2.09 per cent and +1.72 per cent, respectively, in a 20-step CIFAR100 benchmark. Further experiments on CIFAR100 and Tiny-ImageNet confirm the method's effectiveness and simplicity across various settings, demonstrating its potential as a general solution for CL [26].

TABLE II GRADIENT BASED MODELS PERFORMANCE

| Models | Results | | | | | | Datasets |
|---|---|---|---|---|---|---|---|
| | Accuracy (%) / Tasks ($T_i$) | | | | | | |
| | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | Average Accuracy (ACC) $P(t) := \frac{1}{N}\sum_{i=1}^{N} p_i(t)$ | |
| GEM [14] | 89% | 83% | 79% | 86% | 84% | 84% | MNIST Permutations |
| | 88% | 89% | 82% | 80% | 74% | 82% | MNIST Rotations |
| | 71% | 68% | 52% | 57% | 65% | 63% | Incremental CIFAR100 |
| A-GEM [15] | 99% | 97% | 93% | 90% | 87% | 93% | Permuted MNIST |
| | 69% | 57% | 60% | 63% | 61% | 62% | Split CIFAR |
| Adv-GEM [24] | 80% | 72% | 76% | 70% | 72% | 74% | MW4 (EWC + Adv-GEM) |
| | 90% | 85% | 92% | 87% | 86% | 88% | MW4 (PackNet + Adv-GEM) |
| | 75% | 70% | 68% | 74% | 73% | 72% | CW10 (EWC + Adv-GEM) |
| | 90% | 88% | 91% | 87% | 89% | 89% | CW10 (PackNet + Adv-GEM) |
| OGD [16] | 90% | 87% | 92% | 90% | 86% | 89% | Permuted MNIST |
| | 91% | 82% | 79% | 73% | 63% | 77% | Rotated MNIST |
| | 98% | 99% | 98% | 98% | 99% | 98% | Split MNIST |
| UPGD [23] | 80% | 75% | 78% | 74% | 78% | 77% | MNIST |
| | 78% | 72% | 74% | 76% | 75% | 75% | EMNIST |
| | 60% | 66% | 62% | 68% | 64% | 64% | CIFAR10 |
| GradMA [33] | 99% | 97% | 98% | 97% | 99% | 98% | MNIST |
| | 80% | 78% | 81% | 77% | 79% | 79% | CIFAR10 |
| | 66% | 62% | 65% | 60% | 62% | 63% | CIFAR100 |
| | 52% | 50% | 45% | 55% | 48% | 50% | Tiny-ImageNet |
| RWM [30] | 93% | 92% | 93% | 94% | 95% | 93% | CLEAR |
| TS-ACL [31] | 90% | 87% | 85% | 89% | 89% | 88% | UCI-HAR |
| | 94% | 90% | 93% | 91% | 92% | 92% | UWave |
| | 99% | 97% | 98% | 99% | 97% | 98% | DSA |
| | 55% | 60% | 58% | 55% | 57% | 57% | GRABMyo |
| | 85% | 83% | 86% | 82% | 84% | 84% | WISDM |
| SharpSeq (SS) [32] | 56% | 59% | 64% | 62% | 63% | 60% | ACE2005 |
| | 62% | 61% | 62% | 61% | 60% | 61% | MAVEN |

Continual Relation Extraction via Sequential Multi-task Learning (CREST), introduced by Le et al. (2024), designed to mitigate catastrophic forgetting in continual relation extraction (CRE) using a customized multi-task learning framework. CREST addresses the challenge of differing gradient magnitudes across objectives, effectively bridging the gap between multi-task learning and continual learning. Extensive experiments on multiple datasets show that CREST significantly enhances CRE performance and outperforms existing state-of-the-art multi-task learning frameworks. These results highlight its potential as a promising solution for continual learning in relation extraction [27].

Continual Flatness (C-Flat) method, proposed by Bian et al. (2025), is designed to balance the trade-off between sensitivity to new tasks and stability in preserving memory, addressing catastrophic forgetting in continual learning (CL). It achieves this by promoting a flatter loss landscape optimized for CL. C-Flat is a plug-and-play approach that can be seamlessly integrated into any CL method with minimal implementation effort [28].

VERSE, proposed by Banerjee et al. (2024), introduces a novel streaming approach that processes each training example only once, requires a single data pass, supports class-incremental learning, and enables real-time evaluation. The method relies on virtual gradients to adapt to new examples while preserving generalization to past data, mitigating catastrophic forgetting. Additionally, an exponential moving average-based semantic memory is incorporated to enhance performance. Experimental results on diverse datasets with temporally correlated observations confirm the method's effectiveness, demonstrating superior performance compared to existing approaches [29].

Radian Weight Modification (RWM), presented by Zhang et al. (2024), a continual learning approach for audio deepfake detection. RWM categorizes classes into two groups: genuine audio, which exhibits compact feature distributions across tasks, and fake audio, which has more dispersed distributions. These distinctions are quantified by using in-class cosine distance, guiding RWM in applying a trainable gradient modification direction tailored for different data types. Experimental comparisons with mainstream continual learning methods demonstrate that RWM excels in both knowledge retention and mitigating forgetting in deepfake detection [30].

TS-ACL, introduced by Fan et al. (2024), is an analytical continual learning framework designed for time series class-incremental pattern recognition, addressing catastrophic forgetting through gradient-free recursive regression learning. This approach not only enhances learning efficiency but also ensures privacy preservation. Experimental evaluations across five benchmark datasets demonstrate that TS-ACL surpasses existing methods, achieving an optimal balance between stability and plasticity. Additionally, it maintains both the non-forgetting and weight-invariant properties, making it a highly robust solution. Its efficiency and minimal computational requirements make TS-ACL particularly well-suited for resource-constrained environments such as edge computing [31].

SharpSeq (SS), proposed by Le et al. (2024), is a novel framework designed to seamlessly integrate state-of-the-art gradient-based multi-objective optimization methods into continual event detection systems. It effectively tackles challenges such as imbalanced training data and the unique constraints of continual learning, leading to significant performance improvements in event detection over time. Comprehensive empirical benchmarks confirm SharpSeq's effectiveness and adaptability, demonstrating its applicability beyond event detection to a wide range of continual learning tasks across various domains. This work establishes a strong foundation for future research, highlighting the potential of multi-objective optimization in advancing continual learning methodologies [32].

GradMA (Gradient-Memory-based Accelerated), presented by Luo et al. (2023), is a method designed to mitigate catastrophic forgetting in federated learning (FL), particularly in scenarios with data heterogeneity and partial participation. It achieves this by simultaneously refining the update directions of both the server and workers. On the worker side, GradMA utilizes the gradients from the previous local model, the centralized model, and the parameter differences between the current local model and the centralized model as constraints in a quadratic programming (QP) formulation, enabling adaptive correction of the local model's update direction. Meanwhile, on the server side, GradMA integrates memorized accumulated gradients from all workers as QP constraints to enhance the centralized model's update direction. Additionally, theoretical convergence analysis is provided under a smooth non-convex setting, and extensive experiments validate the effectiveness of GradMA in reducing forgetting while improving FL performance [33].

## IV. Discussion

Through the analysis of gradient-based continual learning approaches, it becomes evident that while these methods offer significant progress toward mitigating catastrophic forgetting, they are not without trade-offs. A recurring challenge is balancing computational efficiency with memory usage, particularly when episodic memory buffers are employed. Moreover, the performance of many models in highly dynamic, non-stationary environments remains inconsistent. In practice, real-world continual learning applications such as autonomous agents, real-time surveillance, and personalized healthcare demand models that are both scalable and resilient to noisy or imbalanced data. The research also highlights that no single approach fully resolves the stability-plasticity dilemma, and that hybrid strategies integrating gradient projection with rehearsal, regularization, or adaptive memory may be necessary. We believe future progress lies in the development of lightweight, task-agnostic architectures that can dynamically adapt while maintaining a strong capacity for long-term retention and generalization.

## V. Conclusion

The research presents a comprehensive review of gradient-based approach for mitigating catastrophic forgetting in continual learning. Through an in-depth analysis of key concepts such as continual learning (CL), catastrophic forgetting challenge, and stability and plasticity dilemma. Next, the research highlights the strengths, limitations, and comparative performance of the most common gradient-based models including Gradient Episodic Memory (GEM), Averaged Gradient Episodic Memory (A-GEM), and Orthogonal Gradient Descent (OGD). The findings confirm that gradient-based methods effectively reduce forgetting by strategically adjusting model updates to preserve prior knowledge while integrating new information.

Despite the strong potential of gradient-based approaches in continual learning, they come with notable limitations. First, many of these methods (e.g., GEM, A-GEM, OGD) rely on storing samples from previous tasks, which increases memory requirements and may not be scaled efficiently in memory-constrained environments. Second, their performance may degrade in real-world scenarios where data distributions are non-stationary, unpredictable, or imbalanced. These environments require high robustness, which some gradient-based models currently lack. Third, there is a growing need for novel and hybrid approaches that combine the strengths of gradient projection with adaptive techniques such as attention mechanisms, reinforcement learning, or dynamic memory

allocation to better handle varying task complexities and improve scalability.

Furthermore, despite the progress in continual learning, challenges remain in achieving an optimal balance between stability and plasticity, improving computational efficiency, and enhancing scalability to real-world applications. Future research should explore hybrid approaches that integrate gradient-based learning with replay-based and regularization-based methods, optimize memory utilization, and investigate new architectures that promote long-term knowledge retention without excessive computational costs. By addressing these challenges, continual learning can unlock its full potential, enabling deep learning models to adapt efficiently in dynamic and evolving environments.

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# IoT-Enabled Waste Management in Smart Cities: A Systematic Literature Review

Moulay Lakbir Tahiri Alaoui, Meryam Belhiah, Soumia Ziti
Intelligent Processing and Security of Systems-Faculty of Sciences, Mohammed V University in Rabat, Morocco

***Abstract*—The growing population of cities has increased the pressure on the waste management systems and therefore, new and better approaches are needed. This paper aims to present the theoretical underpinning of the application of Internet of Things (IoT) technologies in the improvement of waste collection in smart cities. In this regard, this paper reviews the latest trends, methodologies, and technologies from a vast collection of peer-reviewed papers published between 2018 and 2024. The areas of focus include real-time monitoring systems, predictive analytics, and optimization algorithms that have created new norms in traditional waste management. The review discusses the novel concept of IoT-based smart bins, dynamic waste collection routing, and data-based decision-making frameworks which yield significant environmental and economic benefits. According to established studies, reported outcomes include reduced overflow and manual labor costs, improved routing efficiency, enhanced recycling processes, optimized bin placement, and increased energy savings. Across a variety of cities, reports comparing pre-IoT operations with IoT-enhanced ones have found remarkable decreases in operating costs, resource allocation, and overall sustainability performance improvements. However, challenges in data security, interoperability and scalability still exist, highlighting the need for a standardized framework and policies. This review contributes to the existing body of knowledge by identifying research gaps and proposing directions for future work. It emphasizes the importance of hybrid approaches combining IoT with emerging technologies such as artificial intelligence and blockchain to address the limitations of current systems. The findings offer valuable insights for policymakers, urban planners, and researchers aiming to foster sustainable and smart urban ecosystems.**

***Keywords*—*Waste management; smart cities; Internet of Things (IoT); smart bins; urban planning***

## I. Introduction

Big cities are facing overpopulation and increasing reliance on the challenges of industrial activities [1], [2]. This requires urgent action, such as in waste management [3], [4]. Overcoming this requires a new approach to waste management [5]. Traditional approaches to waste management is inefficient and results in environmental degradation and inappropriate use of resources [6], [7]. Recent advances in information and communication technology in particular, [8] the Internet of Things (IoT) and artificial intelligence (AI) have improved waste management, such as increasing the efficiency of garbage collection and achieve higher recycling rates [9], [10], [11]. IoT-enabled smart bins use sensors to monitor waste levels in real-time [12], which allows periodic trash collection and avoid overflow incidents [13], [14]. AI algorithms can perform a data analysis that can have insights into optimization of collection routes based on waste generation patterns [15], [16], [17] thus, improving the operational efficiency.

The use of blockchain technology enhances trustworthiness through traceability and transparency when it comes to waste management [18], [19]. There is a move towards a more sustainable approach through recycling and using waste for energy[5], [6]. When it comes to waste sustainability, data quality is key; it also plays a vital role in decision-making[3], [20]. Using comprehensive and real-time data enables predicting trends on waste generation [20] and also allows assessing the impact of waste management practices on the environment.

New technologies help to improve resource usage, as well as to preserve the environment [7]. The effective waste management practices could only be achieved once academia, industry, and policymakers join hands in the quest of developing new and sustainable solutions [2]. The integration of IoT-based solutions in waste management has shown significant improvements in collection efficiency [17] and resource optimization.

Furthermore, the application of artificial intelligence-enabled analytics facilitates the anticipation of waste generation and the optimization of collection pathways [10], [21], [22]. Recent research underscores the significance of sustainable economic frameworks within waste management [23], accentuating the contribution of circular economy strategies [2]. Circular economy frameworks have been extensively examined [24], [25], [26] to improve waste valorization and reduce ecological repercussions.

This paper is organized as follows; the next section describes the research methodology, including the data sources, inclusion and exclusion criteria, and analysis procedures. Section III summarizes the literature and addresses the core research questions through an in-depth review of current practices, technological advancements, and thematic trends. In Section IV, we discuss the key findings, highlight persistent challenges, and suggest relevant directions for future research. The paper is concluded with a summary of key contributions and implications in Section V.

We will demonstrate the used methodology in the study in the subsequent section, and then the relationship between selected papers will be delved into in the synthesis section.

## II. Methodology

Throughout this research, we are carrying out a defined and carefully engineered process to guarantee the exactitude and significance of our results. Fig. 1 encompasses the five main

parts of this study that we are working on. The first step is formulating IoT and household waste collection ideas and holding to the selection of correct criteria and research questions. This stage is the cornerstone of the research, as it is necessary for building a strong study. Phase 2 is about locating studies from the best sources, like ScienceDirect and Scopus, to get exact data. Whereas the Phase 3 is characterized by the use of strict inclusion and exclusion criteria, which allow the selection of only high-quality, English-written literature between 2018 and 2024, then it concentrates on the examination of the different research works, through strategies like categorical analysis and statistical reference to be able to find the coherence in the data. In the fourth phase we will answer to the most important questions in the study, Finally, Phase 5 discusses the findings, challenges and suggestions, and signals the current gaps in research for the future exploration.

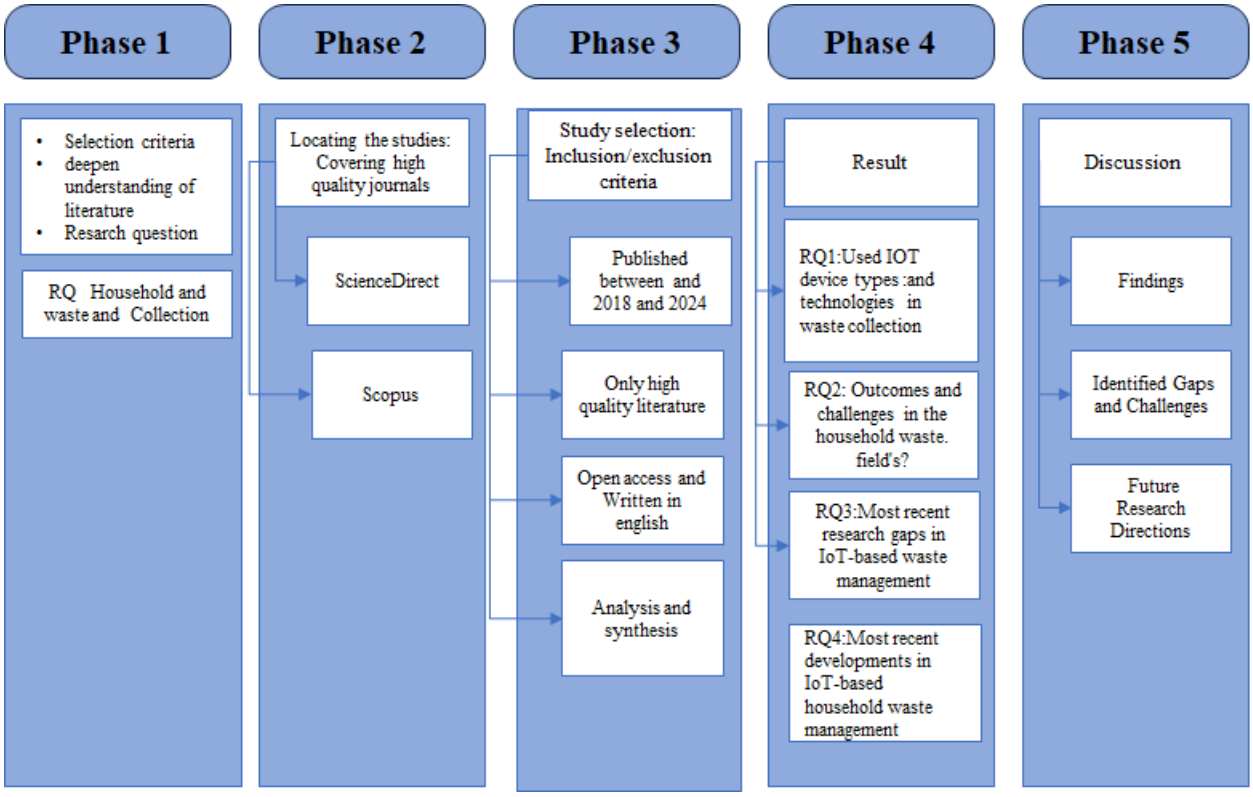


Fig. 1. Research process.

### A. Pilot Search and Data Research Question

We have conducted a preliminary search to get an in-depth overview of IoT applications in urban waste management and mapping of the existing literature in our introductory stage. Sources of relevance were identified by applying a defined search string across the most important and trustworthy electronic databases from different publishers outlined in Table I as described by [27]. The preliminary search also supported the development of inclusion and exclusion criteria for literature selection.

TABLE I RESEARCH QUESTION DETAILS

| Database | Search within | Fields | Search string | Time Span |
|---|---|---|---|---|
| Web of Science | Title, abstract, keywords | All Fields | household waste collection | 2018..2024 |
| Scopus | Title, abstract, keywords | All Fields | household waste collection | 2018..2024 |

### B. Locating the Studies

The utilization of prominent databases and the development of a research question driven by specific objectives are essential for a comprehensive exploration of the literature. To encompass a broad spectrum of documents related to the domain of household waste, a general inquiry is articulated. The Web of Science and Scopus databases are utilized to perform a comprehensive literature review, employing search criteria that encompass open access publications from the period spanning 2018 to January 2025, authored in English, and focusing on innovations and current trends within the research-oriented field regarding household waste collection.

### C. Papers Selection

The preliminary analysis carried out on December 26 discovered 5,100 entries in the Scopus and Web of Science repositories. The two principal parameters employed for the delineation of the search were open-access publications released between the years 2018 and 2024, alongside the specific topic of "household waste collection".

In addition, we included only English-language peer- reviewed journals. Titles, keywords, and abstracts were searched to weed out publications beyond the scope of this study, such as those related to pharmacology, toxicology, chemistry, etc. The reference databases were combined in Rstudio, where 94 duplicate references were removed, resulting in 350 articles for further analysis.

### D. Research Questions (RQ)

Research questions that are both well-structured and answerable are necessary for an exhaustive literature review [28]. These questions serve as the foundation for the entire inquiry and help to create the research design by influencing the kinds of techniques and tactics used [9]. After a thorough literature analysis and multiple rounds of pilot searching, the study's main research question—"How can IoT technologies improve household waste collection systems?"—was refined. To ensure a sharp focus on the inquiry and presentation of all pertinent features, four sub-research questions are developed inside the framework of the above all-inclusive question in order to delve deeper into this inquiry. These include:

- RQ1: What are the different types of IoT device types used in household waste collection?
- RQ2: What are the outcomes and challenges IoT technologies for household waste collection are facing?
- RQ3: What are the research gaps in IoT-based household waste collection domain?
- RQ4: What are the most recent developments in IoT-based household waste management?

### E. Analysis and Synthesis

After getting a good blend of relevant papers, data analysis and synthesis can start. The purpose of the analysis is to take each study apart and map its concepts, while the synthesis focusses on finding cross-study commonalities and patterns. Such efforts forms the basis for an investigation of the applications of IoT on waste management practices in smart cities. Analysis and synthesis of this review are presented briefly in following sub-section.

Out of the 350 articles identified for review, 60 articles contribute to the field of Computer Science, Information Systems, 52 to Environmental Sciences, 48 to Green and Sustainable Science and Technology, 48 to Electrical and Electronic Engineering, and 32 to Environmental Studies, as per Fig. 2, among other fields.

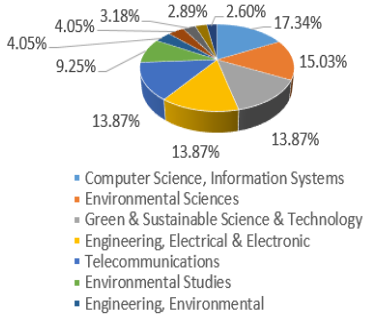


Fig. 2. Field type.

The time span of this review covers a broad range, with the earliest articles dating back to 2018 and the most recent published in 2025 (Fig. 3).

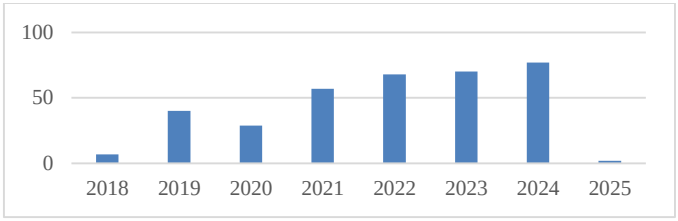


Fig. 3. Time distribution.

## III. Results

This chapter addresses the research questions utilizing data gathered from selected articles.

### A. Answer to the RQ1: What are the different Types of IoT Device Types used in Household Waste Collection?

Household waste management has witnessed the integration of various IoT devices and technologies [29], [30], offering innovative solutions to longstanding inefficiencies. Smart bins equipped with sensors are among the most commonly used technologies [31], [32], enabling real-time monitoring [8] of waste levels and reducing overflow issues [33]. Ultrasonic sensors are used to measure fill levels and Weight sensors to indicate garbage load as demonstrated in urban Malaysia using LoRaWAN networks [3], [34], [35]. Wireless Sensor Networks (WSNs) have also been implemented to enhance waste collection efficiency, where these technologies reduced fuel consumption and optimized routing [7], [36]. Advanced technologies such as AI and cloud computing have been utilized in Egyptian cities to improve waste generation predictions [37], leveraging cellular and Wi-Fi networks for real-time analytics [1], [38]. GPS tracking systems further contributed to waste management by optimizing collection routes and minimizing operational inefficiencies [4], [39], [40], [41] while solar- powered e-waste management solutions have been piloted in Bangladesh to promote recycling efforts using LoRaWAN networks [4], [5]. IoT-enabled optimization routes in Dublin and smart home solutions in Iran have also shown promise in reducing collection times and improving segregation at the household waste level, respectively [3], [7], [42]. These advancements demonstrate the potential of IoT in transforming waste management; Table II summarizes used IoT devices in the selected studies, the use case study geo-location, used technologies, communication methods, power source, the key outcomes, and the identified challenges for each study.

### B. Answer to the RQ2: What are the Outcomes and Challenges of IoT Technologies for Household Waste Collection are Facing?

The integration of IoT in household waste collection has led to significant improvements in efficiency,[1], [43], cost reduction, [5], [44] and environmental sustainability [1]. One of the key outcomes is the optimization of waste collection routes,[36], [45], where smart sensors and AI-driven scheduling enable real-time monitoring of waste levels [46], reducing unnecessary trips and fuel consumption [10]. Several studies highlight the improvement in waste separation and

classification, [47] with smart bins capable of distinguishing between organic, inorganic, and electronic waste, [43], [48] thereby enhancing recycling processes. [5], [49] Additionally, the use of real-time data transmission and cloud computing has enabled the automation of waste monitoring, [5] ensuring timely collection and preventing overflow issues. Cost efficiency is another major outcome, as IoT-driven waste collection systems reduce manual labor costs [4] and improve operational productivity. Furthermore, studies emphasize the role of energy- efficient smart bins, [1] which reduce power consumption while maintaining effective monitoring of waste accumulation. [34] Despite their advantages, these technologies face many challenges, next chapter dives to different challenges IoT devices are facing in household waste management domain.

TABLE II IOT DEVICES AND TECHNOLOGIES USED FOR HOUSEHOLD WASTE COLLECTION

| Study | IoT Technology Used | Network Type | Key Outcomes | City/Country |
|---|---|---|---|---|
| Wong 2023 [3] | Smart bins, Sensors Raspberry Pi 4b as microcontroller. ultrasonic and tracker sensors | Wi-Fi | Reduced overflow, collection and classification of waste, Waste Separation | Urban Malaysia. |
| Abidin 2022 [43] | Sensors | LoRaWAN | Optimal waste bin placement using LoRa Network. Clustering method for waste bin placement. Sort organic and inorganic waste and monitor the volume, gas content, and weight of waste in waste bins | Rural Area in Indonesia |
| Anagnostopoulos 2021 [7] | Not specified | Not specified | Lowered fuel use, new system based swapping full bins for empty ones, real-time scheduling of waste collection, dynamic routing | St. Petersburg, Russia. |
| Ahmed 2023 [1] | AI, Cloud Computing | Not specified | Energy saving, optimal waste collection routes regenerate missing data, High-priority bins require immediate collection | Egyptian cities. |
| Sharma 2020 [9] | In general | In general | Finding barriers: data Security and Privacy High costs of implementation and maintenance, Heterogeneity and Lack of standardization. High energy consumption | India. |
| Okubanjo 2024 [4] | Arduino Uno as controller ultrasonic sensors | Wi-Fi module for data transmission. | Improved efficiency in waste collection processes. Reduced costs associated with manual labor. | Applied in Nigeria. |
| Farjana 2023 [5] | ultrasonic sensor | Cloud, | Separating E-waste, Converting E-waste plastic to bio-fuel and bio-char, improve recycling processes ,monitor waste levels and alert collectors | Tested in Bangladesh. |
| Ghahramani 2022 [2] | In general | microcontroller-based platform | Improved efficiency of waste management in urban areas. Optimizes waste collection routes, real time monitoring | Dublin. |
| Ehsanifar 2023 [6] | IoT in Smart Homes various IoT devices | Not specified | IoT enhances energy efficiency and waste management practices in smart homes | Conducted in Iran. |
| Hussain 2024 [10] | Ultrasonic sensors: fill levels Weight sensors: garbage load | various of networks | Real-time monitoring Ultrasonic Sensors, Weight Sensors: Predictive Routing System | Qatar. |
| Fataniya 2019 [11] | IoT sensors, Node MCU, Ultrasonic Sensor, Moisture Sensor, Gas Sensor | GSM technology | waste segregation and real-time monitoring | Ahmedabad: India. |

### *C. Answer to the RQ3: What are the Research Gaps in IoT-Based Household Waste Collection Domain*

Although the use of IoT technologies in household waste management has brought several benefits, these technologies continue to face challenges that limit their widespread adoption and scalability [50]. Common faced challenges are data privacy issues, limited scalability, incidental network and high implementation cost [9]. These barriers need to be addressed to achieve the full potential of IoT for smart cities environments Table III below summarizes challenges different IoT devices and technologies face:

TABLE III CHALLENGES THAT IOT SOLUTIONS FACE

| Solution/ Technics | Challenges Identified |
|---|---|
| Waste classification [3] | Diversity of Waste Types, Technological Limitations |
| Mobile Depot Implementation [7] | Complex and resource-intensive, Real-Time Data Management, Traffic dependent, Costly solution, High coordination demanded. |
| IoT Waste management barriers [9] | Data quality, Implementation cost, Regulation, energy consumption. |
| Waste management using Smart bins [4] | data integrity and security, public attitude, sorting waste |
| Smart e-Waste classification [5] | Variability in e-waste feedstock. |
| Optimal waste collection routes [1],[2], [5], [39], [36] | Dependent of data accuracy, timeliness, and network connectivity.<br>Optimization Complexity: multiple conflicting variables, Computational cost, Missing data, Big number of trucks: Coordination and Decision-making. |

The use of smart waste management IoT devices such as smart sensors, bins, GPS tracking systems, and RFID tags can significantly reduce the inefficiency of waste collection processes [51]. LPWAN technologies, especially in the case of LoRaWAN technologies, have a wide application in the case of their efficacy and cost-effective coverage. Many studies recommend the use of new technologies (like blockchain and AI) to revolutionize the industry through improved security and preventive measures. Nevertheless, significant hurdles-data privacy, scalability, and network interference remain. Next sub- chapter treats recent developments and research gaps in household waste field.

### *D. Answer to the RQ4: What are the Most Recent Developments in IoT-Based Household Waste Management?*

Recent advancements in IoT-based household waste management have introduced technologies such as smart bins equipped with sensors to prevent overflow and enhance efficiency, as demonstrated by Wong [3]. Blockchain has also been recommended to improve transparency and scalability in urban waste systems, as shown by Okubanjo [4]. AI-driven predictive analytics [52], [53], as highlighted by Ahmed [1], have enabled better forecasting of waste generation, while solar powered IoT systems have emerged to address e-waste recycling challenges, as evidenced by Farjana [5]. Despite these advancements, research gaps persist, particularly in terms of infrastructure, scalability, and data privacy, as reported by Ghahramani [2] and Ehsanifar [6]. Table IV summarizes the recent development and identified gaps, these gaps need further exploration and development.

TABLE IV RECENT DEVELOPMENT AND IDENTIFIED GAPS

| References | Recent Development | Identified Gaps | Study Location |
|---|---|---|---|
| Wong, 2023 [3] | Smart bins with IoT sensors for overflow prevention | High initial cost, scalability challenges, limited adoption in rural areas | Urban Malaysia |
| Okubanjo, 2024 [4] | Blockchain integration for enhanced transparency | Scalability issues, lack of robust infrastructure, user adoption challenges | Nigeria |
| Ahmed, 2023 [1] | AI and cloud computing for predictive waste analytics | Data privacy concerns, high computational requirements | Egyptian cities |
| Farjana, 2023 [5] | Solar-powered IoT systems for e-waste recycling | Lack of infrastructure, insufficient funding for large-scale implementation | Bangladesh |
| Ehsanifar, 2023 [6] | Smart home solutions for waste segregation | User adaptation challenges, limited IoT integration at the household level | Iran |
| Ghahramani, 2022 [2] | IoT-enabled optimization for collection time reduction | Data reliability issues, dependence on battery-powered devices | Dublin |

## IV. DISCUSSION

IoT technology has significantly improved household waste management efficiency, cost reduction, and sustainability. Many studies have demonstrated that IoT-based waste collection systems can monitor waste in real-time, optimize routing dynamically, and automate waste separation, thereby reducing the overall environmental impact. Several cities in India, Malaysia, and Russia deploys ultrasonic sensors and microcontroller-based platforms to optimize waste collection routes, reduce fuel consumption, and improve waste management.

By implementing predictive models and AI-driven scheduling, waste collection logistics have also improved, ensuring high-priority bins receive timely service while preventing overflow. Furthermore, research illustrates how real time data and cloud computing offer municipalities valuable insights that can be used to reduce costs and improve public satisfaction.

Smart waste management systems continue to face several implementation challenges despite recent technological progress. The main implementation obstacle consists of heterogeneous IoT devices and non-uniform communication protocols, which produce challenges for interoperability. Municipal data security and privacy issues create significant risks during systems operation mainly because of sensitive information involved. The high price tag associated with implementing and maintaining these systems limits their spread specifically in developing nations that face strong financial restrictions. The proposed advantages of IoT for waste collection methods face limitations due to the poor public participation in waste segregation and recycling. Research into economical IoT deployment plans, improved cyber security systems and community involvement programs must be conducted to overcome present barriers in sustainable waste management practices.

Although the present study contributes to understanding IoT-based household waste management, it has certain limitations. One key limitation is the dependency on data quality and real-time transmission. IoT devices deployed in waste collection rely heavily on accurate and continuous data flow; however, sensor failures or data transmission errors can lead to inconsistencies in waste monitoring.

IoT-based waste systems requires robust data validation mechanisms and redundancy measures to enhance their reliability. Additionally, findings may not be generalizable. The majority of IoT studies are conducted in urban area, where infrastructure supports IoT deployment. Rural areas with limited connectivity and technology infrastructure face additional challenges. To extend IoT waste management solutions to non-urban environment, alternative network technologies such as LoRaWAN and GSM should be explored. It remains a challenge to optimize bin placement; current methods rely on static actions, though future research could explore AI-driven dynamic models that adapt to fluctuating waste generation patterns. Last but not least, future studies should address long-term sustainability of IoT-based waste management, considering maintenance costs, device longevity, and lifecycle environmental impacts.

### A. Identified Gaps and Challenges

The widespread adoption and effectiveness of smart waste management are hindered by several key challenges. Infrastructure adaptation is among the most pressing issues, for example, mobile depots and IoT-based collection systems require significant changes to existing frameworks, making implementation complex and expensive. On top of that, the majority of research rely on theoretical models and simulations rather than real-world deployment and testing, raising concerns about the lack of real-world validation. The availability of IoT connectivity further complicates the situation, especially in regions with unstable network infrastructure, which affects data collection and communication. Moreover, consumer acceptance and behavioral adaptation are underexplored areas, as public perception and willingness to engage with automated waste systems are critical to their success. AI-driven waste classification and data management process also require optimization, as current systems are not adaptable to diverse and unpredictable real-life conditions. With IoT infrastructure requiring a high initial investment, scalability and cost efficiency remain challenges. Furthermore A lack of standardized metrics makes comparisons, evaluating efficiency, and identifying best practices difficult, Fig. 4 summarizes those challenges.

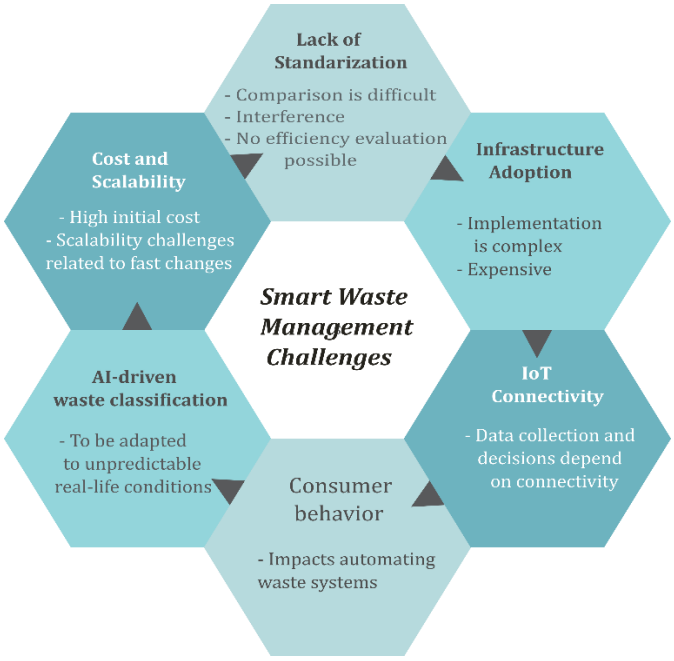


Fig. 4. Challenges in smart waste management.

### B. Future Research Directions

In order to overcome these challenges, future research must enhance AI-based decision-making, particularly by optimizing waste detection, classification, and waste collection routes. To validate theoretical models and refine system performance, extending field implementation and pilot programs across diverse urban environments will be essential. In addition, improving IoT sensor efficiency by developing more reliable, energy-efficient, long-lasting sensors is essential for achieving sustainable long-term deployment.

Understanding public attitudes and participation through behavioral analysis of customers is another essential field of research to improve compliance with smart waste disposal systems. It would also be beneficial to conduct comparative studies between different cities to identify the most appropriate waste management strategies and key success factors. It is imperative that policymakers develop robust regulatory frameworks to foster the adoption of IoT-enabled solutions and push for infrastructure advancements. Lastly, improving the sustainability of smart waste management systems will require exploring alternative energy sources, such as solar-powered waste bins and mobile depots.

Data privacy concerns and reliability issues remain in IoT-based waste management [9]. For instance, enabled optimization systems in Dublin revealed challenges in ensuring consistent and reliable data [2]. Furthermore, privacy concerns associated with AI-driven systems need to be addressed through robust security measures, as noted in Egypt [54]. To bridge these gaps and maximize their impact on global waste management systems, future research should focus on cost-effective, scalable, and secure IoT solutions.

## V. Conclusion

This systematic literature review highlights the significant advancements IoT technologies have brought to household waste management. These technologies poses the potential to optimize operations, improve resource allocation, and enhance sustainability metrics. In the future, more research should focus on developing affordable and scalable IoT solutions to ensure widespread adoption. To mitigate privacy concerns associated with cloud-based processing, enhanced data security measures are necessary. Hybrid approaches combining IoT with AI and blockchain will enhance waste management systems' robustness and efficiency. IoT devices can also become more sustainable by integrating renewable energy sources, such as solar power. It would be possible to establish more robust and efficient waste management systems through the exploration of hybrid approaches that combine IoT with advanced technologies, such as artificial intelligence and blockchain.

Collaboration among stakeholders, including policymakers, urban planners, and technologists, is essential to foster innovation and create standardized frameworks that address the limitations of current systems. These efforts are imperative for building sustainable smart cities that can effectively manage household waste while minimizing environmental impacts.

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# Wireless Internet of Things System Optimization Based on Clustering Algorithm in Big Data Mining

Jing Guo
Shaanxi Institute of International Trade & Commerce, Xi'an 712046, China

***Abstract*—The rapid development of the Internet of Things (IoT) has highlighted the importance of Wi-Fi sensor networks in efficiently collecting data anytime and anywhere. This paper aims to propose an optimized routing protocol that significantly reduces power consumption in IoT systems based on clustering algorithms. The paper begins by introducing the architecture of Wi-Fi sensor networks, sensor nodes, and the key technologies needed for implementation. It distinguishes between cluster-based and planar protocols, noting the advantages of each. The proposed protocol, DKBDCERP (Dual-layer K-means and Density-based Clustering Energy-efficient Routing Protocol), utilizes a two-layer clustering approach. In the first layer, nodes are clustered based on density, while in the second layer, first-level cluster heads are further grouped using the K-Means algorithm. This dual-layer structure balances the responsibilities of cluster heads, ensuring a more efficient distribution of data reception, fusion, and forwarding tasks across different levels. Simulation results demonstrate that the DKBDCERP protocol achieves optimal performance, with the smallest curve value and the most stable amplitude. It significantly reduces energy consumption, with the total cluster-head power consumption recorded at 0.1J and a variance of $0.1\times10^{-4}$. The introduction of two election modes during the clustering stage and the adoption of a centralized control mechanism further contribute to reduced broadcast energy loss. This research introduces an innovative two-layer clustering scheme that enhances the energy efficiency of wireless sensor networks in IoT environments. By leveraging clustering algorithms and a network routing protocol optimized through big data mining techniques, the proposed DKBDCERP significantly reduces energy consumption while maintaining communication stability in large- scale wireless Internet of Things (IoT) systems. The optimized routing protocol provides a novel solution for reducing power consumption while maintaining network stability, offering valuable insights for future IoT applications.***

***Keywords*—Wireless sensor; network routing protocol; clustering algorithm; two-layer clustering; Internet of Things***

## I. INTRODUCTION

The supporting technology of the Internet of Things integrates RFID (radio frequency identification), Sensor technology, Wireless Sensor Networks, intelligent service, and other technologies. The research on the Internet of Things technology is the research on these supporting technologies. In the supporting technologies of the Internet of Things, the emergence of transmission networks with features such as short distance and low power consumption makes it possible to build a ubiquitous network connecting things [1]. Therefore, the lookup of the Wi-Fi sensor community has an irreplaceable role in the area of the Internet of Things. With the non-stop improvement of a variety of conversation technologies, Wi-Fi sensor community technology, which can pick out and attain the records statistics wanted by way of humans at any time, somewhere, and in any environment, has laid a strong basis for the improvement of the contemporary Internet of Things [2]. The wireless sensor community is a multi-hop self-organizing network, which is composed of a giant variety of sensor nodes, which are randomly allotted in monitoring areas and can speak with each other, and is a very necessary technical shape of the underlying community of the Internet of Things [3].

At present, Zhang Lingling et al. proposed a totally dispensed dimension and conversation approach primarily based on match triggering, which permits every node to reap a balance between estimation error and power consumption barring world facts [4]. Luo et al. proposed an intrusion detection algorithm for Wi-Fi sensor networks based totally on laptop learning, which brought the nearby density of information and the distance of record points into fuzzy clustering, enhancing the clustering effectiveness whilst decreasing the clustering convergence time [5]. Liu et al. proposed a quantization strategy for the propagation characteristics of ultrasonic sources. The nodes calculated quantization information according to the quantization strategy and measured values and transmitted the quantization information to the base station, which then estimated the location of the sound source according to the proposed multi-source positioning method based on the possibility mean clustering algorithm [6]. Aiming at this feature of agricultural monitoring, Gao Hongju et al. proposed to apply a clustering algorithm to cluster head nodes for spatial data fusion, and reduce data transmission and energy consumption through clustering [7]. Sun Dayan et al. brought the K-means clustering technique into the positioning hassle of Wi-Fi sensor networks, screened the distance data with giant blunders via cluster analysis, and used the multilateral positioning approach to stumble on and remedy the ultimate distance statistics as the ultimate end result [8].

Despite extensive research on clustering-based WSN routing protocols, most existing approaches suffer from high energy consumption due to single-layer architecture and lack of centralized control. Our work addresses this gap by proposing a two-layer clustering scheme combined with centralized optimization and immune-algorithm-based routing, which significantly enhances energy efficiency and network longevity. Based on the clustering algorithm, this paper proposes an optimized routing protocol for Wi-Fi sensor networks, which notably reduces the strength consumption of IoT systems. Firstly, the shape of Wi-Fi sensor networks, sensor nodes, and the key applied sciences wanted for implementation are introduced. It is pointed out that the two kinds of protocols have

*Corresponding Author

distinctive utility emphases. Cluster-based and planar protocols have their personal advantages, however, cluster-based networks are simpler to study from the benefits of planar protocols. Then, an excessive electricity effectivity WSN protocol DKBDCERP (Dual-layer K-means and Density-based Clustering Energy-efficient Routing Protocol) based totally on two-layer clustering is designed. In the first layer, the nodes of the Wi-Fi sensor community are clustered based totally on density, and in the 2nd layer, the first-level cluster heads are clustered primarily based on K-Means. This double-layer cluster shape can stabilize the tasks undertaken via the cluster heads more, make the center of attention of the first-level cluster head and the second-level cluster head different, distribute the statistics receiving, fusion, and forwarding amongst the cluster heads at all levels, and decrease the power loss of the cluster heads. The remainder of this paper is organized as follows. Section II reviews the architecture and routing protocols in WSN. Section III details the design of the DKBDCERP protocol, including clustering mechanism and routing optimization. Section IV presents the simulation setup and performance evaluation. Section V discusses the implications and limitations of our findings. Finally, Section VI concludes the paper and outlines future research directions.

## II. Wireless Sensor Network Routing Protocol

### A. Wireless Sensor Network Architecture

From the perspective of the whole network, the structure of WSN consists of three parts: a common sensor node, a sink node (base station), and a user management node. The network structure is shown in Fig. 1.

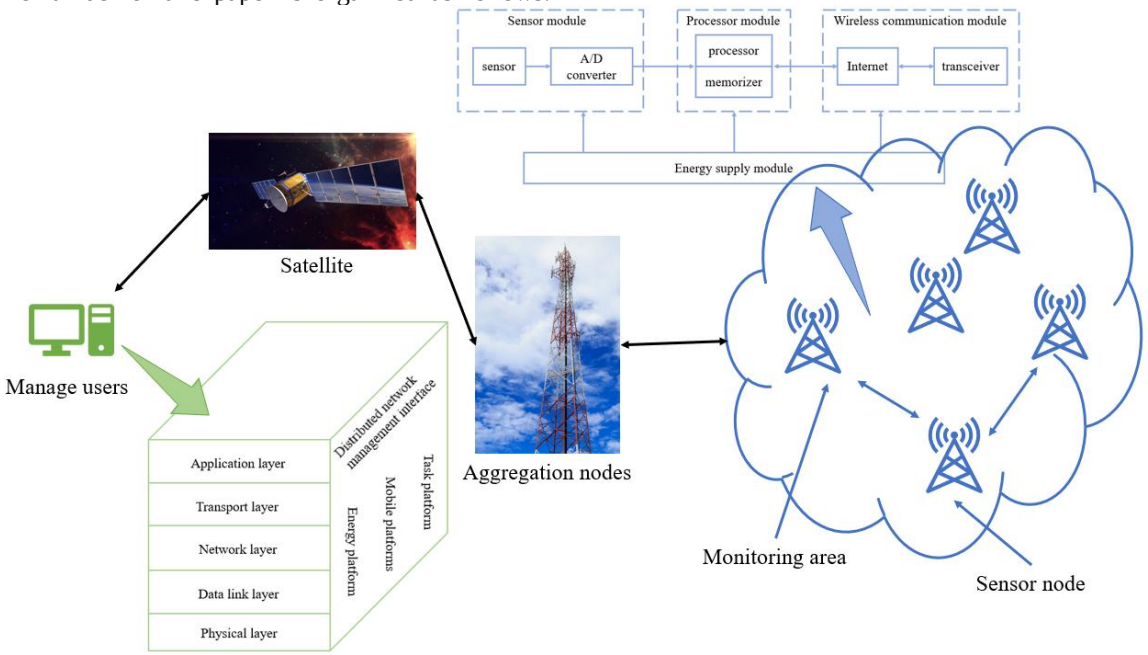


Fig. 1. Network structure of wireless sensor.

As can be seen from Fig. 1, there are sensor nodes in the monitoring area, which are randomly deployed in the monitoring area without any infrastructure support and form a network through their own wireless communication function [9]. Sensor nodes perceive and collect relevant information according to the user's instructions, and each node has the same function. They can communicate with each other, share data information, perform simple fusion processing of the collected data, and then transmit the data to the sink node in the form of a single-hop or multi-hop. Aggregation nodes have no perception ability, but they also have the ability to calculate, store, and transmit data, and this ability is much stronger than that of ordinary nodes [10]. The sink node connects the detection area with the user terminal through satellite and the Internet, transmits the data obtained by the sensor node to the user, receives the user's request for information query, network management, and other tasks, and transmits the command to the sensor node so that the node can collect data according to the user's requirements.

Each sensor node is an embedded design, and the functions of different node designs are different, but the basic structure of the node remains unchanged, mainly composed of four modules: sensor, processor, wireless communication process, and energy supply process [11].

The sensor in the sensor module is responsible for sensing and collecting the information about the monitored object in the monitoring area, and the A/D converter converts the collected analog signal into a digital signal that can be processed by the processor to complete the data acquisition. The processor module mainly processes the information collected by nodes and the information received from other nodes, and then temporarily stores it in the memory [12]. The Wi-Fi conversation module is accountable for the verbal exchange between nodes in the network, and via the Wi-Fi conversation function, the nodes can alternate manage statistics with every other and obtain and ship the gathered environmental information. The power-provided module gives the strength required for the operation of the different three modules via a surprisingly small battery so that the nodes in the community can work normally. Each of the 4 modules is interrelated.

The protocol stack of WSN is similar to the layered structure of other network protocols. The protocol stack is divided into physical layer, data link layer, network layer, transport layer, and application layer from bottom to top. In addition, it also includes three management platforms and distributed network management interfaces, so that sensor nodes can collaborate with each other, so that limited energy can be used efficiently, so that the network can complete the work smoothly in multiple tasks.

### B. Routing Protocol

*1) Plane protocol*: The Information Negotiation Protocol (SPIN) consists of a collection of adaptive protocols. This protocol takes gain of the truth that neighboring nodes have comparable records and honestly distributes facts that different nodes do not. Nodes are assigned a frequent identity to describe the records they collect and are negotiated earlier than statistics are transferred between any nodes [13]. Also, SPIN is in a position to comprehend the modern power degree of the node and regulate the protocol in accordance with the closing energy. These protocols work in a time-driven mode, walking facts throughout the community even if the person has not requested any information. SPIN is designed to tackle the shortcomings of traditional flooding, the use of negotiation, and useful resource adaptation [14]. The SPIN protocol is based totally on two simple ideas: transmitting records that describe perceptual facts is extra environmentally friendly and saves greater electricity than transmitting all data.

SPIN's meta-data negotiation solves the simple flooding problem, which saves a lot of energy. SPIN is a three-step protocol in which sensor nodes exchange three types of messages: ADV (advertisement), REQ (request), and DATA (data transmission). ADV is used to broadcast new DATA, REQ is used to request data, and facts are the data itself. Its special work waft is confirmed in Fig. 2.

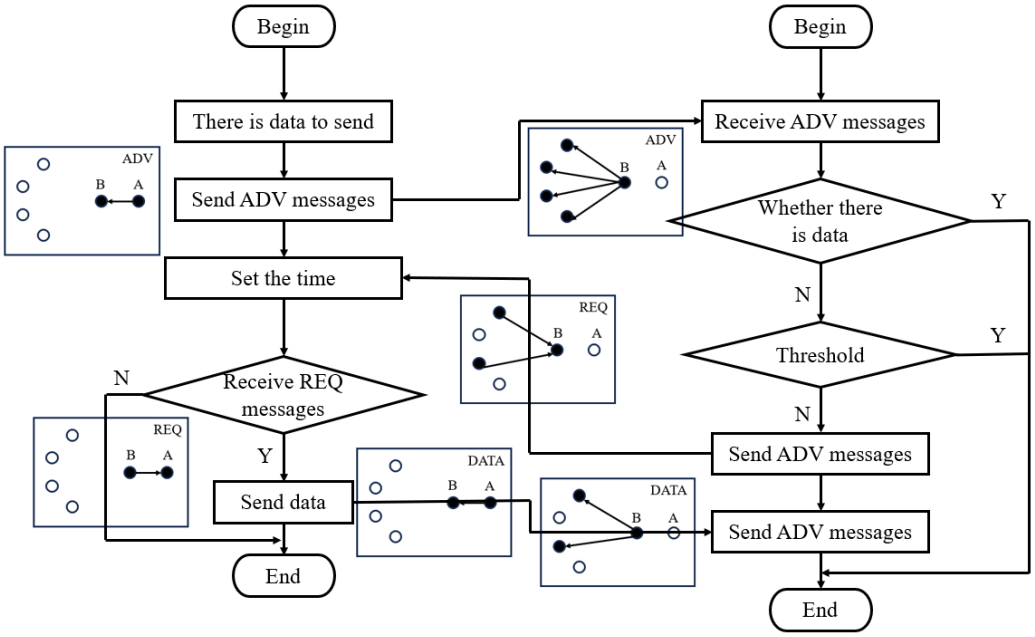


Fig. 2. SPIN workflow.

Directional Fusion Protocol (DD) is a data-centric and application-specific mechanism in the region all facts generated by way of sensor nodes are named by using the capability of attribute fee pairs. The quintessential notion of DD is to mix information from unique sources to restrict redundancy and restrict the variety of required transfers, as a final result saving electrical energy and prolonging the life cycle [15]. Sensors measure occasions and create gradient facts for their respective neighbor nodes. The base station requests statistics through broadcasting interest. Interest refers to the duties that the community is required to accomplish. Interest spreads around the network, hop after hop, every node spreading to its neighbors. As Interest spreads in the course of the network, a gradient is hooked up to describe the statistics that satisfy the question directed to the preferred node [16]. Multiple paths of data drift are formed, and then the fine paths are strengthened to forestall flooding. To decrease conversation consumption, facts are aggregated alongside the path. The intention is to discover a top aggregation course to get the facts to the base station.

*2) Cluster routing protocol:* By dividing the network into clusters, a hierarchical network topology can be obtained. The so-called cluster is a set of a couple of nodes with positive identical properties, which is composed of the cluster head node and cluster participants [17].

The LEACH routing algorithm is the fundamental algorithm of the clustering algorithm. In order to shop community strength consumption, the LEACH algorithm makes use of the cluster as a unit to transmit records to the base station, which reduces the strength consumption of member nodes in the cluster and prolongs the survival time of nodes. The protocol takes "rounds" as the cycle period, and every spherical consists of the cluster formation stage and the steady transmission stage.

At the beginning of a new round, each node in the neighborhood randomly generates a variation between zero and one. Then the neighborhood compares the price of the node with the threshold to pick out the cluster head node. If the threshold is smaller, it can come to be the cluster head node. After the node is conscious that it is the cluster head node, it informs the neighborhood of the information and then waits for distinctive nodes to maintain the records and select whether or not no longer be a phase of the cluster as a cluster member node in accordance with the distance rule. After that, the community is divided into a couple of clusters, which is the cluster formation stage. This is the stable transmission stage. After a certain amount of time, the network will start a new round of repetitive work.

Borrowing the clustering idea of the LEACH algorithm, the PEGASIS algorithm is clustered in the form of a chain and is divided into a unique cluster containing all nodes in the network. Before forming a chain, nodes in the network broadcast power signals to identify their nearest neighbor nodes, which is essential for constructing an energy-efficient chain topology. Using the greedy algorithm, the node farthest from the base station is regarded as the beginning provider of the chain, and the node closest to the node is decided as the subsequent node. The node already in the chain cannot be chosen over and over [18]. And so on, till the chain consists of all the nodes in the network, after which, the cluster head node is chosen and the cluster ends. In the secure transmission stage, the token ring mechanism is used to manipulate the transmission of data, and the frequent node in the chain transmits the amassed facts to its subsequent hop node, and then the subsequent hop node fuses the facts with its personal facts and continues to transmit it downward in this way. Finally, the cluster head node sends all the information to the base station after fusion processing, till a node dies, the spherical ends, and the community at once enters the formation stage of the subsequent spherical chain.

## III. WSN Energy-Efficient Routing Protocol based on Two-Layer Clustering

### A. Wireless Communication Model and Energy Consumption Calculation

The Free-space mannequin assumes perfect propagation surroundings with solely one straight, barrier-free direction between the sender and the receiver. H. Friis proposed to use the following equation to calculate the power depth of the obtained sign in free area at a distance of d from the transmitter.

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \quad (1)$$

In the Free-space model, the communication range is defined by concentric circles centered around the transmitter. A receiver located within this range can successfully receive all packets; otherwise, the transmission fails.

Between two moving nodes, a single straight path is not the only way for a signal to propagate. In the Two-ray ground reflection model, both the linear propagation path and the reflection path of the ground are considered [19]. Over long distances, this model makes more accurate predictions than the Free-space model. When the distance is d, the energy received is approximately:

$$P_r(d) = \frac{P_t G_t G_r h_t^2 h_r^2}{d^4 L} \quad (2)$$

As the distance increases, the strength consumption in the above formula (2) is quicker than in formula (1). However, the two- ray floor reflection mannequin is now not advantageous when dealing with brief distances due to the jitter triggered by the introduction and destruction of the aggregate of two lines. The Free-space mannequin is nevertheless used when the distance d is small.

The electrical energy consumption of the sender is the sum of the strength consumption of the digital computing device of the sending circuit and the strength consumption of the power amplifier, and the energy consumption of the receiver is the strength consumption of the digital machine of the receiving circuit. In the experiment, each the free house mannequin and the double course propagation mannequin are used. When the transmission distance is much less than the threshold, the strength amplification loss adopts the free area model. When the transmission distance is higher than or equal to the threshold, the multipath attenuation mannequin is adopted. The electricity bumps off through the sensor node to transmit Kbit is as follows:

$$E_{Tx}(k,d) = E_{Tx-\text{elec}}(k) + E_{Tx-amp}(k,d) \quad (3)$$

$$E_{Tx}(k,d) = \begin{cases} E_{\text{elec}}{}^{*}k + \varepsilon_{fs}{}^{*}k^{*}d^2 & d < d_c \\ E_{\text{elec}}{}^{*}k + \varepsilon_{mp}{}^{*}k^{*}d^4 & d \geq d_c \end{cases} \quad (4)$$

The energy consumed per Kbit received by the sensor node is:

$$E_{Rx}(k) = E_{Rx-\text{elec}}(k) \quad (5)$$

$$E_{Rx}(k) = E_{\text{elec}} * k \quad (6)$$

In addition, records fusion additionally consumes a sure quantity of energy, and EDA is used to characterize the electricity fed per unit bit of information fusion. We anticipate that the information amassed by way of the neighboring node has excessive redundancy, and the cluster head can fuse its member information into a constant-size packet and then ship it to the sink node.

### B. Clustering Algorithm Analysis and Comparison

LEACH is a classic routing protocol designed in 2000. Based on the idea of clustering, the protocol divides all nodes in the network into multiple clusters, which are composed of multiple sub-nodes and a single head node. Each node randomly generates a decimal between 0 to 1, and whether a node can be selected as the cluster head depends on the comparison between the random number generated and the threshold [20]. When the random count is below the thickness threshold, the node is selected as the head node. The calculation of the threshold value T(n) is as below:

$$T(n)=\begin{cases}\dfrac{p}{1-p^{*}\left(r \bmod \dfrac{1}{p}\right)} & n \in G \\ 0 & \text{otherwise}\end{cases} \quad (7)$$

Here, p is the desired percentage of cluster heads, r is the current round number, and G is the set of nodes that have not been selected as cluster heads in the last 1/p rounds. This ensures that every node has an equal chance of becoming a cluster head over time, and prevents the same nodes from being selected repeatedly, which would lead to premature energy depletion.

However, this randomness can still result in suboptimal energy distribution. In this paper improved protocol, an energy- aware election mechanism is introduced to dynamically adjust the thresholds based on the residual energy of each node, distance from the base station and local density. This multi- factor approach ensures that cluster heads are selected more precisely, improving load balancing and prolonging network lifetime.

In LEACH protocol, the basis unit receives the data sent by the first nail, and the first nail senses and fuses the data sent by the child nail. The whole process drains a lot of power, thus making the task heavier for the first node. To balance the energy loss of the network, the deal rotates the opposite nodes. The time cycle is divided into several rounds, one cycle is a cycle, and each cycle contains two processes, namely: cluster head election, and data stable transmission. However, there are some problems with the LEACH protocol [21]. First of all, the head node is frequently selected, resulting in increased network energy loss. Secondly, each and every node has an identical chance of being chosen as the head node, so it is not possible to pick out the high-quality node as the head node primarily based on the cutting-edge proper situation. Finally, the frequent node transmits data to the cluster head, and the cluster head transmits records to the base station, all of which undertake the mode of single-hop transmission, resulting in too lengthy transmission distance and decreasing the community life.

The k-means algorithm is a classical clustering algorithm primarily based on partition in cluster analysis, which was proposed by means of J.B. MacQueen in 1967. The predominant concept of the K-means algorithm is as follows: given the statistics set containing N statistics pattern points and the variety of clustering classes k, ok facts objects are chosen randomly as the preliminary clustering middle point, and the "distance" (similarity) between the unselected facts pattern factors and the core factor of every category (cluster) is calculated, and clusters with shut distance are added. The common of every cluster (class) is then recalculated as the core point. The distance between every facts pattern factor and the core of the new cluster (class) is calculated once more for comparison, the contributors in the cluster (class) are re-adjusted, and the cluster is up to date iteratively. The manner is repeated till the criterion feature converges or the quantity of iterations ends. The intention is to divide the records set containing *n* pattern factors to be labeled into ok training (class), to which every pattern factor belongs, and the distance between every pattern factor and the category middle of the category to which it belongs is minimal in contrast to the middle factors of different classes.

The formula for calculating the cluster center (mean) of each cluster is defined as follows:

$$z_j = \frac{1}{c_j}\sum_{i \in n_j} x_i, i = 1,2,\cdots,n,\ j = 1,2,\cdots,k \quad (8)$$

The formula for calculating the criterion function (objective function) of the K-means algorithm is defined as follows:

$$J = \sum_{j=1}^{k}\sum_{\substack{i=1 \\ x \in c_j}}^{n_j} \| x_i - z_j \|^2 \quad (9)$$

It can also be expressed as the formula (10):

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n_j} d_{ij}\left(x_i, c_j\right) \quad (10)$$

Formula (10) is pretty general, representing the distance characteristic between the statistics pair and the center. The targets of formulation (9) and components (10) are the same, and each J can converge to the smallest point, at which time the clustering impact is the best. To sum up, J is a criterion feature expressed through the sum of squares of errors, additionally recognized as the goal feature of clustering. The smaller the cost of the function, the smaller the classification error and the higher the clustering effect.

### *C. DKBDCERP, a Dual-Layer Clustering High-Performance WSN Protocol*

DKBDCERP operates in rounds, and each round basically consists of six phases: first-level cluster creation, first-level cluster head election, second-level cluster creation, second-level cluster head generation, inter-cluster route creation, and message delivery. The cluster construction, cluster head determination, and inter-cluster routing are all remembered on the base station calculation control. In the cluster development stage, the first layer of cluster development consists of the usage of DPC-MND to cluster sensor nodes. The 2D layer cluster development consists of the usage of K-Means to cluster the first-degree cluster heads [22]. The 2nd layer of the cluster selects the secondary cluster head, which is used to get hold of the facts from the principal cluster hair and fuse it. According to the distance, power, and deflection Angle of secondary cluster heads, the international most desirable inter-cluster routing is installed with the aid of an elevated immune algorithm.

If nodes are grouped in every round, the ordinary effectivity will be decreased due to giant aid consumption, so in DKBDCERP, the institution of the first layer of clustering is carried out as soon as each and every ten rounds. The institution of the 2d layer cluster is carried out as soon as per round.

DPC-MND is a density-height clustering algorithm based mostly on mutual proximity-MND computes the proximity intensity of the node spread and explores the density top factor of the node spread based totally on the K-nearest neighbor idea. Then, the identified nodes adjacent to the density top factor are

grouped into this cluster, and the nests in the clip are accelerated and regressively grouped according to their proximity, resulting in dynamic clustering based on the density of the node distribution.

In large-scale WSNs, the number of members in each cluster is generally very large. If only one cluster head is selected in the cluster, the cluster head will undertake multiple tasks such as receiving, fusion, and forwarding at the same time, and the burden is too heavy, resulting in severe and premature energy loss of the node. If two cluster heads are used in a cluster, energy consumption will be balanced to a certain extent [23]. But it still doesn't minimize energy consumption. Therefore, it is considered to set up a first-order cluster head in the first layer cluster and a second-order cluster head in the second layer cluster. In this way, the overburden of single cluster heads can be reduced, and the advantages of double cluster head theory can be integrated. The first-level cluster head is accountable for receiving packets from regular nodes in the first-layer cluster. The secondary cluster head is accountable for receiving the information packets dispatched by way of the most important cluster hair, and then forwarding them to the base station through multi-hop interclassed routing.

As mentioned above, the first layer clustering in the DKBDCERP protocol is performed once every ten rounds. However, the node energy will be lost each round due to the corresponding task, if the first node is selected once every ten rounds, there will be a round in which the node energy cannot be used up to perform the corresponding task. Therefore, this chapter selects a new first-level cluster head in the first-layer cluster according to the cluster head selection algorithm after dividing the first-layer cluster every ten rounds.

One-level cluster head election factor algorithm:

$$\lambda_{\text{firCH}} = \mu \frac{E_{\text{res}}}{E_{\text{res}}} + \nu \left( 1 - \frac{d_{\text{tolodes}}}{d_{\text{tollodes}}} \right) \tag{11}$$

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \| x - \mu_i \|^2 \tag{12}$$

As an unsupervised clustering algorithm, the K-means algorithm adopts the execution mode of the initial stage and adjustment stage. In the adjustment phase, the center of each cluster is constantly updated, using the mean value of the data object as the center. This is constantly adjusted until the criterion function (objective function) converges without any significant change and the result is output. The overall algorithm framework is relatively simple and practical, with strong expansibility and scalability, and good robustness. It only needs to provide the number k of data sets and classifications. In the case of suitable data amount and obvious quantification of similarity between data, it is relatively fast and efficient.

Input: first-class cluster head set Cfirst, cluster centroid number k

Output: Clustering result C, each cluster corresponds to centroid coordinates (x, y)

Step l: Determine the initial cluster centroid number k;

Step 2: Based on the relationship between the first order clause head Cfirst and the clause centroid, categorize it into the closest centroid;

Step 3: After all first-level cluster heads Cfirst are classified, the center of mass is recalculated according to the formed class;

Step 4: Repeat steps two and three till the algorithm converges, and then output the clustering end result C and centroid coordinates (x, y). At this point, the 2d layer cluster is complete.

In this chapter, after the first layer cluster is divided each ten rounds, a new first-stage cluster head is chosen in the first layer cluster in accordance with the cluster head decision algorithm. Then the first-order cluster heads are grouped and the second- order cluster heads are chosen in accordance to the centroid of the clustering. The clustering of the major cluster head and the decision of the secondary cluster head are carried out in every round.

The secondary cluster head is more often than not used to get hold of the records from the important cluster head and fuse it and in the end multi-hop ahead to the base station. Therefore, it is crucial to consider the remaining strength of the migrant node, the relationship between the migrant node and the base station, and the relationship between the migrant node and the center of mass in the two-stage cluster head election algorithm. A candidate node is an ordinary node except for the first-level cluster head, which is represented as follows:

$$C_{\text{candidate}} \in \text{Nodes} \cap C_{\text{candidate}} \notin C_{\text{first}} \tag{13}$$

Two-level cluster head election factor algorithm:

$$\lambda_{\text{secCH}} = \mu \frac{E_{\text{res}}}{E_O} + \nu \left( 1 - \frac{d_{\text{tocen}}}{d_{\text{diagonal}}} \right) + \gamma \left( 1 - \frac{d_{\text{tosink}}}{d_{\text{diagonal}}} \right) \tag{14}$$

When sending records between clusters, the secondary cluster head sends the documents to the base station in a multi- hop manner. In the intercluster routing algorithm, each second-level cluster head selects exclusive second-level cluster heads as the subsequent hop, and the impact on the following parameters needs to be comprehensively evaluated, namely, the residual electrical energy of the candidate cluster head, the distance between the candidate cluster head and the nearby cluster head, and the route of the candidate cluster head. The path is represented via the connection between this cluster head and the candidate cluster head and the Angle between this cluster head and the base station [24]. Using energy, distance, and Angle to pick out the subsequent hop can effectively reduce the range of forwarding hops and verbal trade conflict. Based on the above three factors, this paper constructs the route weight matrix between the secondary cluster head and the base station. Then, in accordance with the matrix, the Dijkstra algorithm is used to generate the preliminary suboptimal path, and the global most environment-friendly route is calculated in accordance with the prolonged immune algorithm.

A numerical two-dimensional routing matrix D[i][j] is described to characterize the directional power from factor i to

factor j. i,j= 1,2,... n,n+1. The n cluster heads are sorted according to their distance from the base station, and the base system is in the first place. The directional weights among the factors are expressed as follows:

$$D[i][j]=\begin{cases}0, i=j\\ 1e-6, i<j\wedge i=0\\ \mu\left(1-\frac{E_{j\,res}}{Eo}\right)+ve^{(d-d_0)/100}+\gamma\frac{\theta_{ij}}{\pi}, i<j\wedge i\neq 0\vee i>j\wedge j>0\\ 1e-6, i=1\wedge j=0\wedge d_{itos}<d_0\vee i>1\wedge j=0\wedge d_{itos}<d_0\\ ve^{(d-d_0)/100}, i=1\wedge j=0\wedge d_{itos}\geq d_0\vee i>1\wedge j=0\wedge d_{itos}\geq d_0\end{cases} (15)$$

According to the immune algorithm principle, Dijkstra was used to generate the initial suboptimal path when generating the initial suboptimal path. Finally, according to the distance of each starting node, the next hop is modified, and the globally optimal path satisfying the lowest energy consumption is obtained.

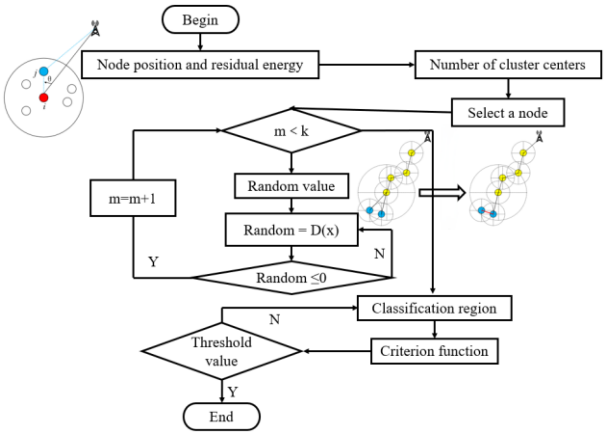


Fig. 3. Algorithm flow chart.

As proven in Fig. 3, when discovering the route from the cluster head to the base station, the route from the cluster head to the base station with a shut distance between beginning nodes solely satisfies the shortest course from this factor to the base station. However, from the perspective of energy consumption of all nodes, it is not the optimal path. Therefore, the immune algorithm is improved in this paper, where the distance between adjacent starting nodes is less than the threshold γ (γ=45 in this paper). When modifying the next hop, check whether the high-energy node already points to the low-energy node. If yes, do not modify the next hop. Otherwise, modify the next hop node to avoid loops.

## IV. Simulation Analysis

This chapter uses Python to simulate WSN and analyzes and compares related protocols. In the comparison experiment, LEACH and recent routing protocols EBCRP, KBECRA, and DBSCAN cluster-based routing protocols were used. The reasons for comparison are as follows: LEACH is more classic. The head node selection of EBCRP takes into account the distance between the node and the base station, so as to reduce the phenomenon of energy holes around the base station, which has the same purpose as the protocol in this chapter. KBECRA uses a double cluster head similar to this chapter and also uses K-means clustering. DBSCAN and DPC-MND used in this chapter both belong to density clustering algorithms.

The test in this chapter runs most of 2,000 rounds. If the variety of surviving nodes in the community is much less than 20 per cent, the community shape is viewed to be significantly damaged. At this time, the simulation ends. See Table I for analog settings.

TABLE I Simulation Parameters

| Argument | Value |
|---|---|
| Number of nodes | 1000 |
| Network detection range | 600*600 |
| Base station coordinates | 300, 650 |
| Initial node energy | 0.5 |
| Rf energy consumption coefficient | 50 |
| Signal amplification energy consumption in the free space model | 10 |
| Signal amplification energy consumption under multipath attenuation model | 0.0013 |
| Data fusion energy consumption | 50 |
| Data fusion ratio | 0.6 |
| Control message length | 200 |
| Data message length | 4000 |

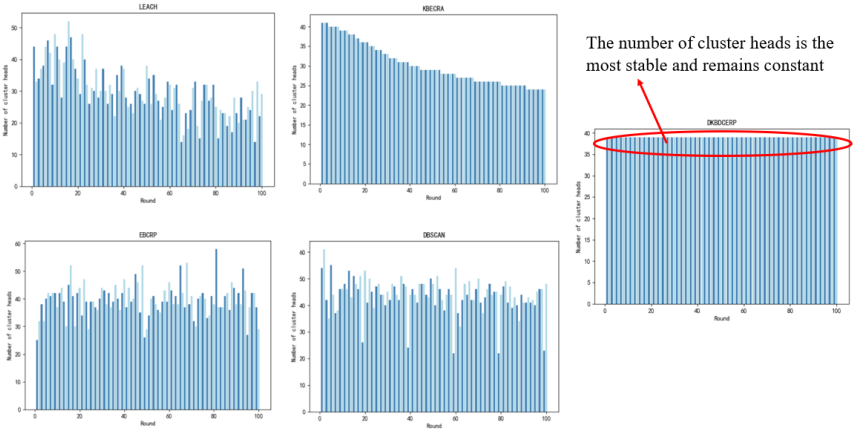


Fig. 4. Cluster head adjustment.

As you can see from Fig. 4, the wide variety of every head varies radically in LEACH. The motive is that the cluster head decision is random in LEACH. Moreover, due to the fact the wide variety of cluster heads is now not optimal, the electricity consumption of the community is increased, the quantity of surviving nodes is reduced, and the quantity of cluster heads is much less and less. EBCRP and DBSCAN reflect on the consideration of the insurance of cluster heads and successfully manage the wide variety of cluster heads. Therefore, the wide variety of cluster heads is very concentrated. Although the quantity of EBCRP clusters is dispensed around 40, it nevertheless fluctuates greatly. The distribution number of DBSCAN cluster heads ranges from 46 to 47 and fluctuates greatly, so the performance of DBSCAN cluster heads in energy consumption is relatively average. Although the wide variety of clusters in KBECRA fluctuates little, due to the speedy power consumption, the range of surviving nodes and the number of clusters additionally reduce rapidly, so the impact is now not good. However, the number of DKBDCERP clusters suggested in this article is steadily assigned to the most suitable ones, with good cluster effects, slow power consumption, and no longer having a wide variety of clusters as soon as KBECRA opens the game. Therefore, the DKBDCERP proposal has superb dependability.

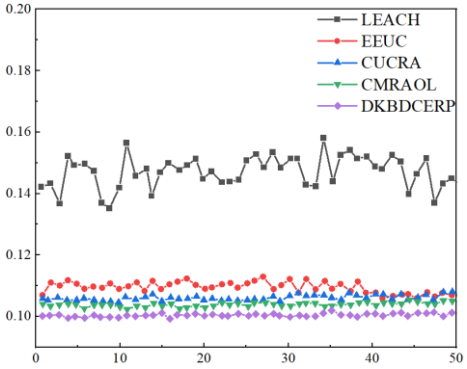


Fig. 5. Cluster head energy consumption.

As seen in Fig. 5, the curve value of the DKBDCERP protocol in this paper is the smallest, and the curve amplitude is the most stable, for the following four reasons. 1) The DKBDCERP protocol is based on grid minimum energy consumption. In the cluster establishment stage, the election mode is changed twice, and the additional broadcast energy consumption is reduced by using a centralized control mechanism. 2) The election of cluster heads tends to be constant cluster centroid coordinates, that is, the distribution of cluster heads is greater uniform and reasonable. 3) The wide variety of participants in every cluster location is fixed, that is, earlier than the node death, the electricity consumption in every cluster head is nearly the same. 4) The hierarchical mechanism is adopted when the cluster head transmits data, which reduces the conversation distance required for transmission. The simulation effects exhibit that the multiplied protocol can limit the electricity consumption of every cluster head.

As can be seen from Fig. 6, the amplitude of the LEACH protocol is the largest, and the curve fluctuation is the most obvious, indicating a large difference in energy consumption between cluster heads. However, the variance of electricity consumption of the EEUC protocol is considerably smaller than that of the LEACH protocol, and its curve fluctuation is smaller than that of the LEACH protocol, due to the fact the cluster dimension of the EEUC protocol is different. Therefore, the strength consumption of all cluster heads in the community is successfully balanced. CMRAOL protocol improves the cluster head election mechanism of EEUC, making it take into account the distance of the Sink. However, in contrast with the EEUC protocol, the cluster head power consumption is reduced. However, the protocol did not enhance the cluster structure, so the electricity consumption hole between cluster heads used to be no longer appreciably improved. It indicates that the strength consumption variance overall performance of the DKBDCERP protocol in this paper is the best, indicating that the power consumption amongst cluster heads is extra uniform, and the purpose is comparable to the strength consumption evaluation consequences of the identical cluster head. In this paper, the non- uniform cluster partition shape is adopted to make the strength consumption of every layer cluster head extra balanced. Moreover, the constant quantity of member nodes makes the strength eaten up by means of intra-cluster conversation extra stable, so the curve amplitude of the protocol in this paper is the lowest and the amplitude adjustments the least.

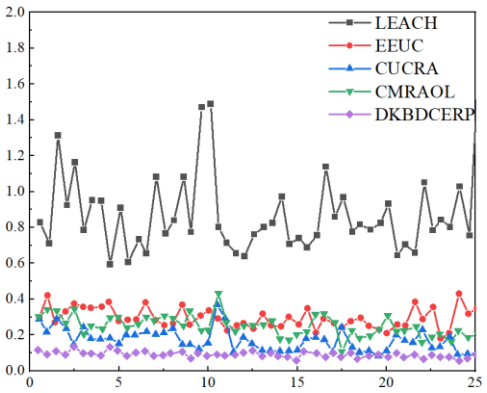


Fig. 6. Variance of energy consumption at cluster head.

## V. Discussion

The proposed DKBDCERP protocol demonstrates high energy efficiency and reliable network longevity. Its dual-layer architecture reduces the burden on individual cluster heads and enhances routing flexibility. However, the model assumes homogeneous sensor capabilities and does not account for node mobility or dynamic environmental conditions. Future research should explore heterogeneous networks, adaptive parameter tuning, and machine learning-based optimization to further generalize the protocol's applicability.

## VI. Conclusion

A variety of routing protocols for the Internet of Things have been proposed, but most of these protocols are for specific application environments, can only improve some specific performance in the network, and cannot take into account the energy consumption of the network. Based on the K-Means algorithm, DKBDCERP, a dual-layer clustering high-performance WSN protocol, is proposed in this paper, which greatly reduces the energy consumption of Internet of Things systems. Specific conclusions are as follows.

An excessive electricity effectivity WSN protocol DKBDCERP based totally on double-layer clustering is designed. In the first layer, the DPCMND algorithm is elevated via mutual proximity and distance, which can dynamically cluster in accordance with the node distribution density, and make the range of first-level cluster heads nearer to the base station increase, which avoids the power gap around the base station to a sure extent. At Layer 2, mass, residual energy, distance, and intermediate values of different elements are utilized to select the secondary cluster heads, and then a novel course right weight is developed to replace the Euclidean proximity, and the Dijkstra algorithm is augmented by adding the concept of image immunization algorithms to it to get the world's most cutting-edge direction.

Simulation results show that the number of DKBDCERP clusters suggested in this article is assigned gradually at the highest quality worth, the effect of clamping is good, and the intensity is consumed slowly, so that the clusters are now varied, and do not show a decreasing style as KBECRA did at the beginning. Therefore, the DKBDCERP protocol has high reliability.

In this paper, the power consumption variance performance of the DKBDCERP protocol is the best. The whole strength consumption of cluster heads is 0.1J, and the electricity consumption variance is 0.1×10-4, indicating that the strength consumption amongst cluster heads is surprisingly uniform. In this paper, the non-uniform cluster partition shape is adopted to make the electricity consumption of every layer cluster head greater balanced, and the constant quantity of member nodes makes the electricity consumption of intra-cluster verbal exchange extra stable.

In future research, we plan to investigate the integration of reinforcement learning techniques to dynamically optimize clustering and routing decisions. Additionally, we aim to extend the current framework to support heterogeneous sensor networks and adapt to real-time environmental changes. A prototype implementation in a physical IoT testbed will also be considered.

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# Hybrid-Optimized Model for Deepfake Detection

H. Mancy[1], Marwa Elpeltagy[2], Kamal Eldahshan[3], Aya Ismail[4]
Department of Computer Science-College of Engineering and Computer Sciences, Prince Sattam Bin Abdulaziz University, Alkharj 11942 Saudi Arabia[1]
Department of Mathematics-Faculty of Science (Girls) Al-Azhar University, Cairo, Egypt[1]
Systems and Computers Department, Al-Azhar University, Egypt[2]
Mathematics Department, Faculty of Science Al-Azhar University, Egypt[3]
Mathematics Department, Tanta University, Egypt[4]

***Abstract*—The advancement of deep learning models has led to the creation of novel techniques for image and video synthesis. One such technique is the deepfake, which swaps faces among persons and then produces hyper-realistic videos of individuals saying or doing things that they never said or done. These deepfake videos pose a serious risk to everyone and countries if they are exploited for extortion, scamming, political disinformation, or identity theft. This work presents a new methodology based on a hybrid-optimized model for detecting deepfake videos. A Mask Region-based Convolutional Neural Network (Mask R-CNN) is employed to detect human faces from video frames. Then, the optimal bounding box representing the face region per frame is selected, which could help to discover many artifacts. An improved Xception-Network is proposed to extract informative and deep hierarchical representations of the produced face frames. The Bayesian optimization (BO) algorithm is employed to search for the optimal hyperparameters' values in the extreme gradient boosting (XGBoost) classifier model to properly discriminate the deepfake videos from the genuine ones. The proposed method is trained and validated on two different datasets; CelebDF-FaceForencics++ (c23) and FakeAVCeleb, and tested also on various datasets; CelebDF, DeepfakeTIMIT, and FakeAVCeleb. The experimental study proves the superiority of the proposed method over the state-of-the-art methods. The proposed method yielded %97.88 accuracy and %97.65 AUROC on the trained CelebDF-FaceForencics++ (c23) and tested CelebDF datasets. Additionally, it achieved %98.44 accuracy and %98.44 AUROC on the trained CelebDF-FaceForencics++ (c23) and tested DeepfakeTIMIT datasets. Moreover, it yielded %99.50 accuracy and %99.21 AUROC on the FakeAVCeleb visual dataset.***

***Keywords*—Bayesian optimization; deepfake detection; deepfake videos; Mask R-CNN; Xception network; XGBoost***

## I. Introduction

The recent developments of autoencoder [1] and generative adversarial networks (GANs) [2], [3] have raised the generation of realistic images and videos. Deepfake techniques can manipulate a human's identity, attributes, or expressions and produce high-quality forged still images and videos. FaceSwap and DeepFaceLab are now the two most often used public open-source software tools for creating deepfakes. They are supported by thousands of users who contribute to developing and enhancing the software and models. Although the technology is used for amusing purposes as in movies or smartphone apps, it also has an evil side when it is employed to create realistic porn videos, spread falsified news, or create fake evidence.

Deciding the video's authenticity can become a top priority when a video pertains to national security concerns. Rapid advancements in video creation methods enable low-budget opponents to utilize commercial machine learning (ML) tools to produce realistic phony content. Therefore, there is a need for a deepfake detection methodology that can keep up with the development of deepfake creation methods, and properly discriminate deepfake videos against genuine ones.

This research presents a new methodology for detecting deepfake videos. It attempts to explore artifacts and visual discrepancies within video frames and decides if a certain video is authentic or deepfake. The Mask R-CNN has achieved effective and accurate performance on several object detection and segmentation benchmarks; the Cityscapes dataset COCO challenges [4], [5], and the WiderFace dataset. It has been demonstrated to be more precise than popular detectors; single-shot multi-box detector (SSD) and You Only Look Once (YOLO) in COCO [6]. It produces fewer false positives compared to YOLO. Additionally, it is more accurate in identifying the object and also offers segmentation information [7]. Consequently, the Mask R-CNN is suggested to be utilized as a detector to extract human faces from frames. This is followed by selecting the optimal bounding box representing the face area for each frame attempting to find a variety of artifacts. The convolutional neural network (CNN) is known to learn and extract discriminative local features effectively. It has been proven to be efficient in recognizing synthesized images and videos. Thus, an improved Xception-Network is employed to generate a deep useful spatial representation of the detected face frames. It assists in discriminating between authentic and deepfake videos. A single-layer classifier built using CNN's activation function may not always be the ideal option for classification. Instead, the sophisticated XGBoost model can overcome the single classifier's shortcomings in feature classification and provide strong predictive performance [8], [9], [10]. The XGBoost is a tree-based boosting ensemble method. Its basic goal is to iteratively combine several weak classifiers into a stronger and more precise classifier [11]. Thus, XGboost is applied here on the extracted features from the improved Xception-Network to check the authenticity of videos. The majority of ML algorithms rely on a variety of hyperparameters. Selecting effective hyperparameters; hyperparameter optimization, is

crucial in ML since these parameters have a significant impact on the model performance. Hence, the BO algorithm is utilized to time-efficiently search for good hyperparameters of the XGBoost model. This helps to prevent overfitting and improves the deepfake detection model performance. The contributions of this research can be summarized as follows:

- The Mask R-CNN is employed to detect human faces from video frames. The optimal bounding box to represent the facial area per frame is then chosen in an attempt to find more artifacts. This assists to enhance the effectiveness of determining videos' authenticity.
- A hybrid optimized model using an improved Xception-Network and XGBoost with the Bayesian optimization algorithm is presented. This extracts distinctive information from the detected human faces, prevents overfitting, provides more precise predictions, and helps to distinguish deepfake videos from authentic ones. This ensures the maximum performance of the detection method.
- A comparative analysis with state-of-the-art deepfake video detection methods is conducted using several evaluation measures; accuracy, recall, precision, F measure, specificity, sensitivity, and Area Under Receiver Operating Characteristic (AUROC) curve metric.

The rest of the paper is structured as follows: Section II presents the related works for deepfake video detection methods. The proposed method and materials to detect deepfake videos are introduced in Section III. The experiment results and analysis are presented in Section IV. Section V is dedicated to the conclusion and future work.

## II. Related Works

Recently, with the development of the internet over the world, the transmission of misleading information has increased significantly. The online media are seen to be tampered with to deceive the public. The progress of advanced artificial intelligence models in manipulating digital information has made it impossible to differentiate authentic media from the falsified with the naked eye. The deepfake technique uses deep-learning algorithms to swap faces or objects in digital content and videos, which convincingly generates realistic fake media. This has prompted the development of methods to detect deepfake media [12], [13]. Deepfake detection methods can be grouped into four types; physiological/physical-based methods [14, 15, 16, 17, 18], signal-based methods [10, 19, 20, 21, 22, 23, 24, 25], data-driven methods [26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38], or methods that are based on combining both signal and data-driven methods [39, 40, 41]. The physiological/ physical based detection methods reveal deepfake videos depending on the observation that synthesized videos lack direct knowledge of humans' physiological characteristics or the physics laws of the surroundings. The signal-based detection methods explore anomalies at the signal level caused by a deepfake generation process. They typically treat videos as a series of frames and a synced audio signal if the audio clip is available. The data-driven methods employ labelled videos; authentic or fake, to train deep learning models that can distinguish deepfake videos from authentic ones [42].

Gazi et al. [14] proposed a DeepVision algorithm for detecting deepfake videos based on analyzing the changes in eye blinking patterns. Blinking patterns fluctuate according to four factors: human gender, cognitive behavior, age, and time; AM, or PM. These factors are extracted per video. The Fast HyperFace algorithm is used to detect faces from video frames and localize landmarks. The eye-aspect-ratio algorithm is employed as an eye tracker to measure the eye blinking count, period, and elapsed blink time. The method finds and compares pattern information that matches the corresponding four factors in the pre-configured database of natural movements with the output of measured blinking per video to decide whether the blink is genuine or artificial. The four extracted factors are employed as search criteria for DeepVision's database. Elhassan et al. [17] presented a method to detect deepfake videos based on utilizing mouth and teeth movements per video frames as biological signal features. The dlib library is employed with the face detection algorithm to detect faces. The mouth-aspect-ratio technique is used to crop the opened mouth region from the detected face frames. The openness of the mouth is detected by determining 12 points representing the upper and lower lips. A CNN with six layers is used to extract features from mouth frames and then detect the deepfakes. Genuine videos are characterized by subtle motion signals that are not precisely replicated by different generative models. Consequently, the work in [18] leverages motion magnification to concentrate on differences in facial sub-muscular motions between genuine and fake videos. It combines traditional and deep motion magnification techniques to distinguish between genuine and fake video; as well, it also identifies the source generator of fake video based on generative artifacts.

The work in [20] employed two approaches to differentiate camera images from Generative Adversarial Network (GAN) based images. The first one is an Intensity Noise Histograms (INH)-based method using the rg chromaticity space. The second one is measuring the frequency of over exposed and under-saturated pixels as features in each image. Then, these features were fed into a linear Support Vector Machine classifier to detect the fake imagery. Zhang et al. [21] introduced a fake imagery detection method based on Spectrum Domain Features instead of the raw RGB image pixels. They employed the 2D Discrete Fourier Transform method on each channel of the RGB image to get a frequency spectrum image per channel. Then, the logarithm of the spectrum is computed and normalized to be fed into the fake imagery classifier to detect the artifacts and classify whether the image is fake or not. The Resnet-34 model with ImageNet is employed for the detection task. In addition, they presented AutoGAN, a GAN simulator that synthesizes GAN artifacts in the images and helps to train the classifier without requiring fake images for training or needing access to a pre-trained GAN model for creating fake images. In [25], a new deepfake video detection method was presented. It leveraged temporal phase variations across video frames using Complex Steerable Pyramid (CSP) decomposition. The output is then passed to a trainable spatiotemporal filter to detect motion cues suitable to

distinguish deepfakes. After that, the ResNet-18 is employed to extract informative features, and the multi-scale temporal convolutional network is employed to capture facial temporal dynamics.

The work in [28], introduced a 3D CNN-based deepfake detection method. It used the RetinaFace to detect the faces from videos. It extracted the motion features from the adjacent video frames using the 3D CNN. The 3D CNN was composed of 3D residual blocks. It proved their efficiency in capturing spatial and temporal information. Agnihotri [29] employed the dlib to align and resize the face images. Then, three pre-trained CNNs were utilized for feature extraction; InceptionV3, EfficientNetB4, and InceptionResNetV2. This was followed by the Long Short-Term Memory (LSTM) network to classify fake and genuine images. Javed et al. [37] proposed to combine eye movement analysis with two deep learning models, MesoNet4 and ResNet101, to detect subtle and complex manipulations in deepfake videos. In [38], two deep-learning models, InceptionV3 and InceptionResNetV2, with the multilayer perceptron classifier, were presented to discern the authentic content from the deepfake one.

The work in [39], proposed to exploit the environmental artifacts to detect the deepfake videos via using texture feature-based method; local binary patterns. In addition, it employed the high-resolution network-based method to automatically learn the significant multi-resolution features from video frames. The features produced from both branches were combined and then fed into the capsule network for the final decision. Ismail et al. [40], proposed to use the Histogram of Oriented Gradient (HOG)-based CNN method to target some specific artifacts; visible splicing boundaries, for detecting the deepfakes. This discovered the distinction between the spatial HOG feature of the real and deepfake video frames. Additionally, an ameliorated XceptionNet was applied to video frames to automatically capture the hierarchical feature representations. The output features of both directions were merged to be fed into GRUs sequence and fully connected layers to detect the inconsistencies and temporal incoherence among the video frames, and then distinguish the deepfake videos from the real ones. In [41], three layers were introduced. The first layer was the RGB features extraction, which was employed to determine the potential forgery signs within the spatial video frames. It applied XceptionNet with an attention module on the cropped face regions resulting from using the dlib library. The second layer was the GAN features extraction, which was employed to detect forgery fingerprints in the high-frequency domain that were left by the GAN process. The final layer was utilized for feature extraction from the inner and outer areas of the manipulated part within a video frame.

Most deepfake detection methods suffer from the overfitting issue in the training data and lack to generalize well across various datasets and manipulation approaches. The proposed method aims to overcome these drawbacks. It uses the Mask R-CNN as a face detector, which is followed by selecting the optimal bounding box representing the facial region that could help to find more artifacts. It also presents a hybrid-optimized model. This model employs an improved Xception-Network to extract distinguished information. Additionally, it employs the XGBoost with the Bayesian optimization algorithm. The XGBoost is an ensemble model that could overcome the limitations of a single classifier. The BO can find the optimal hyperparameters of XGBoost which helps to avoid overfitting, produce more accurate predictions, and effectively distinguish deepfake videos from genuine ones. The proposed method is evaluated on two different datasets created using various manipulation methods. It surpassed previous methods and attained generalization.

## III. Methods and Materials

The suggested deepfake video detection method is composed of the following stages: data pre-processing, deep feature extraction, and optimization-based classification. The three stages are depicted in Fig. 1 and will be described in detail hereafter.

### *A. Data Pre-Processing Stage*

In this stage, the videos are converted into a sequence of frames. Then, the faces are detected and cropped from the frames if these frames are not face-centered. This is because most faking methods concentrate on creating forgery faces. The Mask R-CNN is employed here for face detection. It is a general and flexible framework for object instance segmentation. It is an improved version of the Faster R-CNN [43]. The mask R-CNN is characterized by locating objects from images while also producing a top-notch segmentation mask per object. It predicts a bounding box, a class label, and a mask for each instance in an image [44].

The Mask R-CNN is used here as follows. *First,* various levels of feature maps are extracted from the video frames using the last convolution layer of the ResNet-50 CNN's fourth phase. *Next,* the Feature Pyramid Network (FPN) [45] is utilized to ameliorate the feature extraction process by combining various scale features of the frame. The FPN consists of two paths: bottom-up, and top-down. The bottom up path is the usual CNN that is used for extracting four feature map sets. As going ascendingly, the spatial resolution declines. The semantic value of layers rises with more high-level structures discovered. The top-down path is used to build high-resolution layers out of a semantically rich layer. The lateral connections are added between these reconstructed layers that have more semantic properties and the corresponding feature maps to assist the detector in precisely predicting the objects' location. They serve as a skip connection to simplify training. Thus, the FPN produces multi-scale feature maps that have better information, and enhances the detection model performance. After that, the Region Proposal Lightweight Network (RPLN) employs the mechanism of a sliding window to scan these produced feature maps to find Regions of Interest (RoI) that contain the target object; human face. The sliding window consists of anchors that represent its center points. For each anchor, the RPLN produces two outcomes; foreground or background class, and a refined bounding box that perfectly fits the object. The foreground class indicates the box contains the object. To avoid overlapping multiple bounding boxes and ignore the redundant ones, a non-maximum suppression algorithm that is based on the intersection-over-union metric (1) is adopted to

retain the bounding box with the highest target confidence score.

$$intersection - over - union = \frac{area_{P\_RoI} \cap area_{G\_Bb}}{area_{P\_RoI} \cup area_{G\_Bb}} (1)$$

where, $area_{P\_RoI}$ represents the predicted RoI area, $area_{G\_Bb}$ refers to the ground truth bounding box area, and ∩ and ∪ indicate the overlap and union area of the two regions, respectively [46]. Thus, the RoI is positive, if the intersection-over-union metric is larger than 0.5. The region represents a negative bounding box if this metric is smaller than 0.5. This means the negative region is a background because it does not include the target foreground object. Following this, the final proposal regions are fed into a deep classifier and a regressor, and generate two outcomes. The first outcome is a specific object class, and the second one is a more refined bounding box that encapsulates the object better.

In addition, the RoI alignment layer is employed to correctly align the extracted feature maps with the input and preserve spatial locations. It is proposed in [44] to address the misalignment issue that results from using RoI pooling layer during the operations of the two-integer quantification in the Faster R-CNN. In detection and classification tasks, the RoI pooling layer is usually used after the convolutional layers. It can generate fixed-length feature map from each region and can then be forwarded to the next layers. However, the RoI pooling has a drawback. After a number of convolutional layers, the regions' position and size might be floating-point numbers, and there is a need to split the regions into fixed-size features. The RoI pooling rounds down these floating numbers into the nearest integer values. There are two rounding-down operations. The candidate region's coordinates are quantified to an integer. The quantified RoI is then split into k × k bins, and each bin is quantified once more. This may cause the localization precision to be lost. It generates misalignments between the region and the final extracted feature map. These misalignments have negative effects on the problem of detecting objects. The RoI alignment layer is another manner to obtain a fixed-size feature map from each region, but it retains the floating-point numbers in the operation. It eliminates all quantifications and uses bilinear interpolation resample method to generate accurate values. Thus, in the RoI alignment, the candidate region boundary coordinates are not rounded to retain the floating numbers. As well as, each RoI is split into $k \times k$ bins, and each bin is also not rounded. The bilinear interpolation is utilized to compute $n$ sampled fixed points in each bin, and then the average or maximum pooling operation is performed to obtain alignment results representing this bin [47], [48], [49], [50], [51].

The bilinear interpolation method consists of two steps [4]. In the first step, the linear interpolation is performed in the x-axis direction as follows, using Formula (2) and (3):

$$f(x, y_1) = \frac{x_2 - x}{x_2 - x_1} f(x_1, y_1) + \frac{x - x_1}{x_2 - x_1} f(x_2, y_1) \quad (2)$$

$$f(x, y_2) = \frac{x_2 - x}{x_2 - x_1} f(x_1, y_2) + \frac{x - x_1}{x_2 - x_1} f(x_2, y_2) \quad (3)$$

In the second step, the linear interpolation is performed on the y-direction as follows, using Formula (4):

$$f(x, y) = \frac{y_2 - y}{y_2 - y_1} f(x, y_1) + \frac{y - y_1}{y_2 - y_1} f(x, y_2) \quad (4)$$

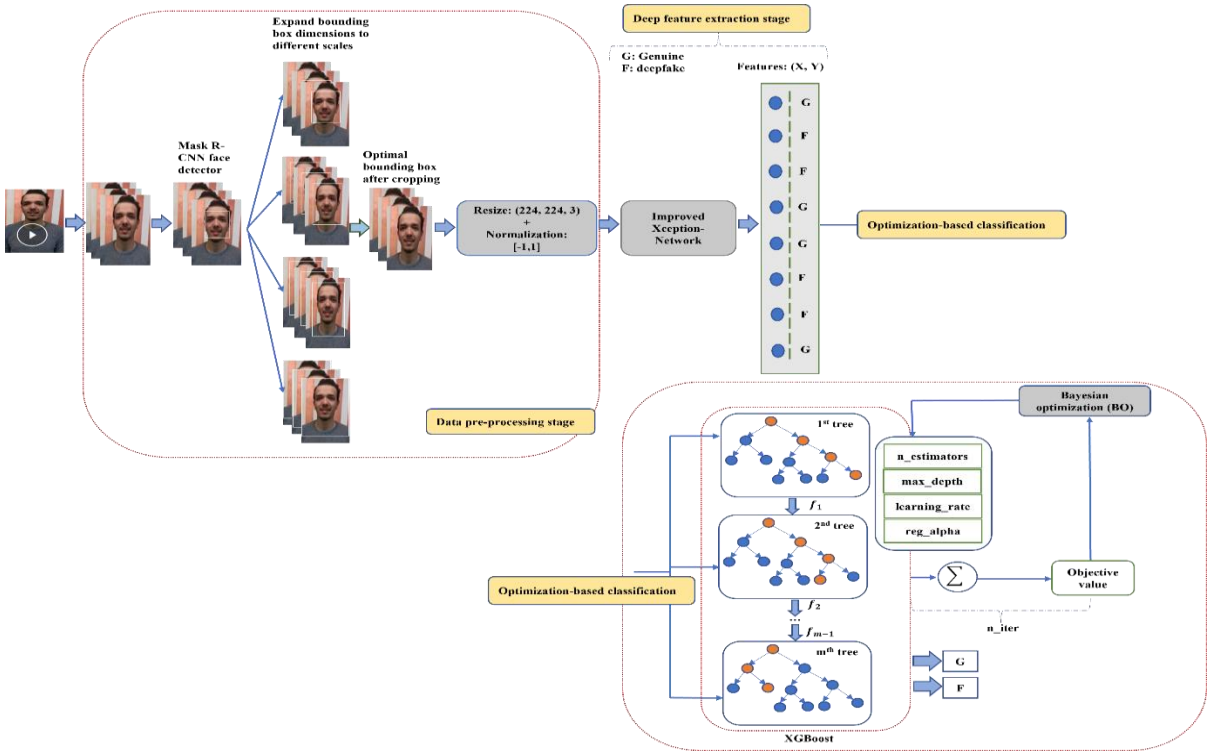



Fig. 1. The proposed deepfake video detection method architecture.

where, $f(x_1, y_1)$ , $f(x_2, y_1)$ , $(x_1, y_2)$ , and $f(x_2, y_2)$ indicate nearby grid points values, $f(x, y)$ represents the sampling point value, and $f(x, y_1)$ and $f(x, y_2)$ refer to the values produced from interpolating on the x-direction. Finally, the RoI alignment output is fed into fully connected layers for the operations of localization and classification. The architecture of the Mask R-CNN to detect faces from video frames is depicted in Fig. 2.

The resulting bounding box which localizes the face is very tight to the front. Thus, as shown in Fig. 1, the produced original bounding box's size is expanded by 7%, 14%, 21%, 28%, and 35% in proportion to its area to occupy a sizable portion of or all the head and neck that could potentially hold artifacts. These bounding boxes of different sizes are employed to crop and extract the face frames. This tries to find the optimal bounding box representing the face area, which helps to reveal as many artifacts as possible.

After the face frames are extracted from videos, they are resized to 224 × 224 × 3 and normalized in the range [-1, 1] to fit the next stage. The output of this will be the input to the coming stage to extract deep video features.

### B. Deep Feature Extraction Stage

The detected videos' face frames that have the shape (224 × 224 × 3) are taken as input to the suggested improved Xception-Network where 224 refers to height and width values and 3 indicates the RGB channels for each frame. The architecture of the traditional Xception-Network depends on depth-wise separable convolutional layers. These layers not only allow for a considerable reduction in the parameters' number but also allow for the independent learning of spatial and channel correlation. It consists of three main phases. The first phase comprises one convolutional block and three separable convolutional blocks with skip connections. The second one consists of eight separable convolutional blocks that have also linear shortcut connections. The final phase comprises two separable convolutional blocks; one of them with residual connection around it and the other does not include it. These linear skip connections seek to stop the gradient from vanishing while the network is being trained [52]. The traditional Xception achieved good performance for facial image forgery detection [53].

The architecture of the suggested improved Xception-Network is shown in Fig. 3. Three convolutional blocks are added to the original architecture before the final rectified linear unit (relu) that followed the final separable convolutional block. These convolutional blocks include convolution layers with filters 1536, 1024, and 1536, respectively, and kernel of size (3, 3), batch normalization layers, and relu activation layers except for the last block. All the convolution layers' inputs are padded with a value of 0 to maintain the grid size. The convolution layers' filters provide feature maps with connections to the local area of the preceding layer. Thus, the convolution output is calculated by convolving the input $(inp)$ with the filters as expressed in the following Formula (5) [54]:

$$x_i = inp * w_i + b_i, i = 1,2, \dots, n \quad (5)$$

where, $n$ represents the number of convolution filters, and $x_i$ indicates the feature map output corresponding to the $i^{th}$ filter. The $w_i$ denotes the learnable parameters of the $i^{th}$ convolution filter, and $b_i$ represents the $i^{th}$ bias. The convolution layers provide effective spatial hierarchal representations of the input. The batch normalization normalizes the input via the entire batch by subtracting its mean and dividing by its standard deviation. Then, these normalized values $(\hat{x}_i)$ are scaled and shifted per channel using the following Formula (6) [54]:

$$y_i = \gamma \hat{x}_i + \beta \quad (6)$$

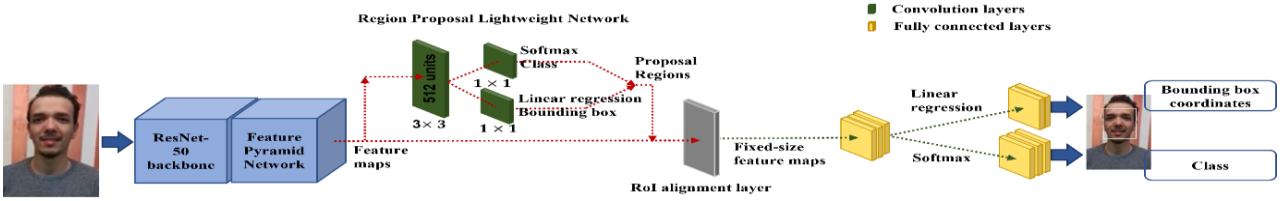



Fig. 2. The Mask R-CNN architecture for face detection.

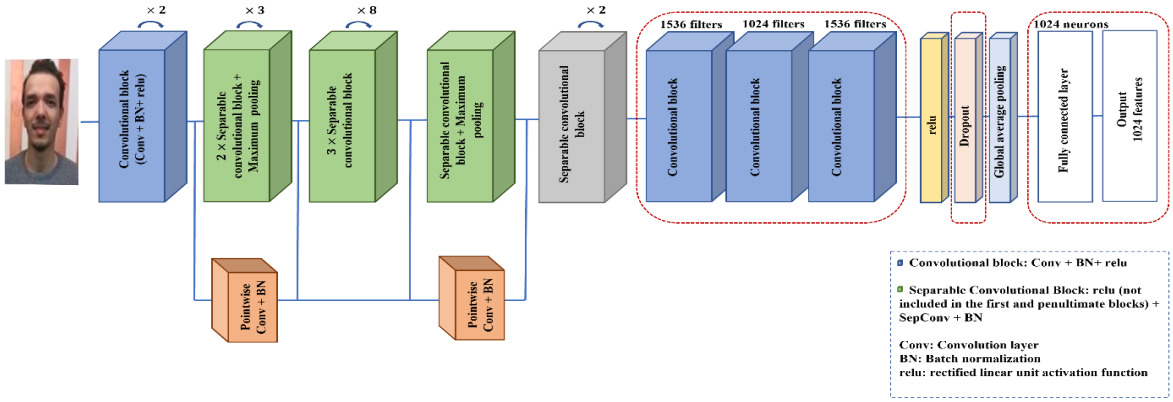



Fig. 3. The architecture of the suggested improved Xception-Network.

where, $y_i$ represents the output value, and $\gamma$ and $\beta$ represent the scale and offset factors that can be learned during the training. The batch normalization speeds up the training, assists in minimizing the diminishing gradient problem, and improves the model generalization. The relu activation function $(f)$ outputs a zero value for negative features to boost the network's nonlinear properties. It is defined as follows, using Formula (7):

$$f = \text{maximum}(0, y) \tag{7}$$

where, $y$ denotes the relu's input value. It helps to speed up training and causes sparsity in the hidden units by squeezing values between zero and maximum [55]. Additionally, a dropout layer is added between the relu that followed the final separable convolutional block and the global average pooling layer to drop out randomly selected nodes with a probability of 20% per weight update. It has been adopted to diminish the effect of overfitting. After that, a fully connected layer with 1024 neurons and relu activation function is added. It is defined as follows, using Formula (8):

$$y_i = f\,(\,w_1 x_1 + \cdots + w_k x_k\,) \tag{8}$$

where, $x_k$ denotes the $k^{th}$ input to the fully connected layer, and $y_i$ represents the $i^{th}$ output from this layer. The $f\,(.)$ indicates the relu activation function, and $w_*$ represents learnable weights in the network. The fully connected layer provides learning capabilities from all features' combinations of the preceding layer.

By applying the proposed improved Xception-Network on face frames, the output per frame is 1024 features constituting a vector representation. The proposed improvements on the Xception-network assists to produce a more valuable spatial hierarchical representation of face frames. This enhances the effectiveness of the deepfake detection method in real settings.

### C. Optimization-Based Classification

After the improved Xception-network effectively extracted valuable spatial features per video, the XGBoost model optimized by the BO algorithm is adopted to distinguish the deepfake videos from the genuine ones. This contributes to overcoming the limitation of a single-layer classifier, preventing overfitting, and ameliorating the overall deepfake detection model's performance.

The XGBoost is employed for classification and regression tasks. It is based on the gradient-boosting approach. The input to the XGBoost can be expressed using Formula (9):

$$S = \{(x_i, y_i)\}, i = 1,2, \ldots, n \tag{9}$$

where, $x_i$ represents the $i^{th}$ sample's features, $y_i$ denotes the truth label, and $n$ represents the samples' number.

The XGBoost model continuously adds a decision tree to learn a new function each time; $f(x)$, to fit the residual of the prior tree. After the model is trained, $M$ trees are produced where the leaf node of each tree corresponds to a prediction score. The sample's final predicted value can be obtained by adding these scores corresponding to every tree. This can be defined as follows, using Formula (10):

$$\widehat{y_i} = \sum_{m=1}^{M} f_m(x_i), f_m \in F = \{f(x) = w\} \tag{10}$$

where, F represents the set space of all trees, and $\widehat{y_i}$ refers to the predicted value. The $f(x)$ refers to a single tree, and the $w$ denotes the leaf nodes' weight score per tree. Since the XGBoost aims to learn these $M$ trees, the following objective function should be minimized, using Formula (11):

$$F(y) = \sum_{i=1}^{n} l(y_i, \widehat{y_i}) + \sum_{m=1}^{M} \Omega\,(f_m) \tag{11}$$

where, $l(y_i, \widehat{y_i})$ represents the training loss function that measures the difference between the estimated and target scores. The $\Omega\,(f_m)$ denotes the penalty term which can help prevent overfitting, and it is expressed as follows, using Formula (12):

$$\Omega\,(f_m) = \gamma K + 0.5\lambda \sum_{j=1}^{K} {w_j}^2 \tag{12}$$

where, $K$ represents the leaves' number, and $\gamma$ refers to a hyper-parameter employed to control the model's complexity by controlling the leaves' number. The $w$ denotes the leaves' weight score, and $\lambda$ is used to make sure the leaves' score is not excessively high.

Since a new decision tree is iteratively added during the training, the XGBoost model at each iteration step $(t)$ updates the objective function as follows, using Formula (13):

$$F(y)^{(t)} = \sum_{i=1}^{n} l(y_i, \widehat{y_i}^{(t-1)} + f_t(x_i)) + \Omega(f_t) \tag{13}$$

This objective function is minimized by applying the Taylor method. The first three terms of the Taylor expansion are taken by the XGBoost, and the extremely small high-order terms are ignored. Thus, the objective function is transformed into the following, using Formula (14):

$$F(y)^{(t)} \approx \sum_{i=1}^{n} [l(y_i, \widehat{y_i}^{(t-1)}) + g_i f_t(x_i) + 0.5 h_i {f_t}^2(x_i)] + \Omega(f_t) \tag{14}$$

where, $g_i$ represents the first derivative of the objective loss function and $h_i$ denotes its second derivative. These derivatives help to fit the residual error. Since the $l(y_i, \widehat{y_i}^{(t-1)})$ term has no impact on the objective function's optimization, it is eliminated. Thus, the objective function is rewritten as follows, using Formula (15):

$$\begin{aligned} \tilde{F}(y)^{(t)} &\approx \sum_{i=1}^{n} \left[ g_i f_t(x_i) + 0.5 h_i {f_t}^2(x_i) \right] + \gamma K + 0.5\lambda \sum_{j=1}^{K} {w_j}^2 \\ &= \sum_{j=1}^{K} [(\sum_{i \in I_j} g_i) w_j + 0.5(\sum_{i \in I_j} h_i + \lambda) {w_j}^2] + \gamma K \\ &\sum_{j=1}^{K} [G_j w_j + 0.5(H_j + \lambda) {w_j}^2] + \gamma K \end{aligned} \tag{15}$$

where, $I_j = \{i\}$ represents the data points indices set assigned to the $j^{th}$ leaf node. The tree model iteration process can be considered as the leaf nodes iteration. The score of the optimal leaf node can be computed as follows, using Formula (16):

$$w_j = -\frac{G_j}{H_j + \lambda} \tag{16}$$

Finally, the objective loss function can be calculated as follows, using Formula (17):

$$\tilde{F}(y) = -0.5 \sum_{j=1}^{K} \frac{{G_j}^2}{H_j+\lambda} + \gamma K \quad (17)$$

One of the most important concepts in machine learning is a parameter, and in the training, the model attempts to discover the appropriate parameters that help to obtain better performance. Hyperparameters are examples of such parameters. A hyperparameter controls the model's complexity or its learnability. Since having appropriate hyperparameters ameliorate the learning models' performance, optimizing them is significant.

Traditionally, hyperparameters optimization mainly depends on a trial-and-error manner and practical experience. Recently, optimization algorithms are employed to find satisfactory optimal hyperparameters. Random search, and grid search are popular examples of such optimization algorithms. The random search algorithm is slightly faster compared to the grid search algorithm, but it does not produce optimal results after optimizing the hyperparameters. The grid search optimization algorithm is very slow. On the other hand, Bayesian optimization [56], is a probabilistic-based optimization algorithm that globally seeks to maximize or minimize the objective function; $\max|min_{x\epsilon H} f(x)$ where, $H$ represents the search space. It is flexible and powerful due to its probabilistic model [57, 58, 59, 60, 61, 62]. Therefore, the BO algorithm is employed here to search for the optimal hyperparameters' values of the XGBoost model. These values minimize the objective loss function of the XGBoost and improve the overall performance of the proposed method.

First, hyperparameter space; $H$, is defined by exploring the range of input values specified for each hyperparameter. The hyperparameter values could be continuous, categorical, or integers. The BO algorithm builds a probabilistic model of the objective function, utilizes this model to choose the next sample point to acquire, and updates the model based on this new sample point and its true objective function assessment [63]. It mainly consists of three steps: probabilistic model, acquisition function, and update process.

The probabilistic model; $p(f(x))$, can be defined as a distribution over the objective function for approximation. It gives an estimation of the objective function. Here, the probabilistic model is the Gaussian Process (GP) due to its analytic tractability and descriptive power [64, 65]. A GP is formally defined as a group of random variables where, each finite subset follows a multivariate normal distribution. Thus, the distribution over $f(x)$ in the GP is defined as follows, using Formula (18):

$$f(x) \sim N(\mu(x), \mathrm{c}(x) = k(x_n, x_m)) \quad (18)$$

where, the function $\mu(x)$ represents the mean and $c = k(x_n, x_m)$ represents the covariance. The $k$ denotes the positive-definite kernel that specifies how points in the input space are correlated. Here, the Matern kernel [66, 67] is employed. The covariance function controls how observations affect the prediction.

The acquisition function is a metric that determines which hyperparameter value can cause the function to return the optimal value. It is employed to measure the evaluation effectiveness at any $x$. The acquisition function can be considered a guide to searching for the optimum. Its role is a trade-off between exploration and exploitation. The GP model's mean indicates the exploitation of the model's knowledge. The GP model's uncertainty indicates exploration due to the model doesn't have enough observations. Thus, the acquisition function uses the mean and the standard deviation of the function $f(x)$ at every $x$ to calculate a value that represents how desirable it is to sample again at this location. The Upper Confidence Bound (UCB) is one such simple acquisition function that aims to weigh the importance between the mean and the uncertainty of the GP [68]. Its formula is defined as follows, using Formula (19) [69]:

$$\mathrm{UCB} = \mu(\mathrm{x}) + \beta\, \sigma(x) \quad (19)$$

where, $\beta$ >0 is the learning rate hyperparameter that manages the preference between exploitation and exploration.

### D. Dataset

The proposed method has been trained and validated on two datasets: CelebDF-FaceForencics++ (c23) [10],] 26], [40] and FakeAVCeleb [70], while it has been tested on CelebDF, DeepfakeTIMIT [71], and FakeAVCeleb. The CelebDF-FaceForencics++ (c23) dataset was created based on combining two popular datasets: the CelebDF and the FaceForencics++ (c23). 2848 genuine and deepfake visual videos of the CelebDF-FaceForencics++ (c23) are used to train and validate the proposed method. 518 genuine and fake visual videos of the CelebDF are used to test the proposed method. This mimics real-world situations due to CelebDF has high-quality visual deepfake videos that closely match those shared online. In addition, to confirm the robustness of the proposed method, 640 genuine and high-quality fake videos of the DeepfakeTIMIT dataset are also used to test the proposed method. Its fake videos are created using GAN-based face swapping techniques. Moreover, 1215 genuine and deepfake visual videos of the FakeAVCeleb are used to train, validate, and test the proposed method. Its genuine videos are varied in gender, age, and ethnic groups, and its fake videos are generated using different manipulation methods. This makes this dataset more realistic. All these datasets help to ameliorate the generalization of the proposed method in real scenarios.

## IV. Experimental Results and Analysis

The proposed method to detect deepfake visual videos is trained and validated using CelebDF-FaceForencics++ (c23), and FakeAVCeleb datasets. It is tested using CelebDF, DeepfakeTIMIT, and FakeAVCeleb datasets. Evaluation metrics [72], [73]: accuracy, recall, precision, F-measure, specificity, sensitivity, and AUROC curve metric, are employed to assess the proposed method's performance. The following experiments are conducted:

Experiment 1: In this experiment, the proposed method is applied to the CelebDF-FaceForencics++ (c23) visual videos dataset. Since the frames of this dataset are not face-centered, the Mask R-CNN is used here for face detection. Different

scales of bounding boxes representing faces are produced. Then, the proposed method's performance is evaluated per scale and the best result is recorded in Table II. It confirmed that expanding the original tight bounding box representing the face by 28% in proportion to its area to occupy a large portion of the head and neck helps to reveal more artifacts and improves performance.

The XGBoost model contains the following hyperparameters: n_estimators, max_depth, learning_rate, and reg_alpha. The n_estimators hyperparameter represents the number of the model's iterations which expresses the number of decision trees that will be generated. The max_depth represents the maximum depth of the decision tree. This constrains the maximum number of children that each tree's branch can have. The learning_rate represents the amount by which the weights are changed each time a tree is constructed. It manages the weighting of newly added trees to the model and prevents overfitting. The reg_alpha represents the L1 regularization term on weights. These hyperparameters constitute the search space that is used by Bayesian optimization to search for the optimal hyperparameters' values of the XGBoost. The range value adopted for each hyperparameter is shown in Table I.

TABLE I RANGE VALUES FOR THE XGBOOST HYPERPARAMETERS DURING BAYESIAN OPTIMIZATION

| HYPERPARAMETER | Range |
|---|---|
| n_estimators | (10, 300) |
| max_depth | (5, 35) |
| learning_rate | (0, 1.0) |
| reg_alpha | (0, 1) |

The validation AUROC score is utilized here during the Bayesian optimizer as the objective to be maximized. The number of model iteration times; n_iter, is selected as 70. This number refers to the number of hyperparameter combinations that are drawn from the search space. The result of each iteration on the CelebDF-FaceForencics++ (c23) dataset is recorded in Table II. The optimal set of hyperparameters is obtained at the forty-sixth iteration. Its value is: 0.023807687602778738 for learning_rate, 6.919040104018402 for max_depth, 299.5191634881166 for n_estimators, and 0.9287421690707279 for reg_alpha.

Finally, the XGBoost model is trained with these obtained optimal hyperparameters' values on the deep extracted features of the CelebDF-FaceForencics++ (c23) to minimize the objective loss function. The proposed method performance is evaluated on the CelebDF and DeepfakeTIMIT testing sets, and recorded in Table III. It achieves %97.88 accuracy, %97.68 recall, %99.12 precision, %98.39 F-measure, %98.27 specificity, %97.68 sensitivity, and %97.65 AUROC on the CelebDF test set. It yields %98.44 accuracy, %98.12 recall, %98.74 precision, %98.43 F-measure, %98.75 specificity, %98.12 sensitivity, and %98.44 AUROC on the DeepfakeTIMIT test dataset.

Experiment 2: In this experiment, the proposed method is applied to the FakeAVCeleb visual videos dataset. Its frames are face-centred and cropped. The number of model iteration times; n_iter, is selected as 10. The result of each iteration on the FakeAVCeleb dataset is recorded in Table IV. The optimal set of hyperparameters is obtained at the fourth iteration. Its value is: 0.25030643979197587 for learning_rate, 5.004759697203255 for max_depth, 151.11064359914357 for n_estimators, and 0.12147201179549794 for reg_alpha. The XGBoost model is then trained with these final optimal hyperparameters' values on the extracted features of the FakeAVCeleb visual videos dataset. The proposed method performance is evaluated on the FakeAVCeleb test set and recorded in Table V. It yields %99.50 accuracy, %100 recall, %98.97 precision, %99.48 F-measure, %99.06 specificity, %100 sensitivity, and %99.21 AUROC.

The confusion matrix visualization of the proposed method on CelebDF-FaceForencics++ (c23) training set with CelebDF and DeepfakeTIMIT testing sets, and FakeAVCeleb visual videos datasets is shown in Fig. 4. The ROC curve and the AUROC curve metric of the proposed method on CelebDF-FaceForencics++ (c23) training set with CelebDF and DeepfakeTIMIT testing sets, and FakeAVCeleb datasets are seen in Fig. 5. The ROC curve is very close to the upper left corner confirming the maximum performance of the proposed method. In addition, the high value of the AUROC curve metric also indicates better model performance.

TABLE II THE AUROC VALIDATION SCORE FOR EACH HYPERPARAMETER COMBINATION ON THE CELEBDF-FACEFORENCICS++ (C23) DATASET

| ITERATION | learning_rate | max_depth | n_estimators | reg_alpha | AUROC score |
|---|---|---|---|---|---|
| 1 | 0.4085 | 24.05 | 160.5 | 0.3467 | 0.9708 |
| 2 | 0.2247 | 21.98 | 220.9 | 0.6408 | 0.9735 |
| 3 | 0.9311 | 29.74 | 23.34 | 0.8362 | 0.9687 |
| 4 | 0.1335 | 34.4 | 11.02 | 0.9807 | 0.9587 |
| 5 | 0.09204 | 34.81 | 227.9 | 0.5098 | 0.9706 |
| 6 | 0.5368 | 5.32 | 11.9 | 0.9079 | 0.9675 |
| 7 | 0.9837 | 33.53 | 240.2 | 0.09379 | 0.9675 |
| 8 | 0.1178 | 5.799 | 83.88 | 0.9184 | 0.9712 |
| 9 | 0.1696 | 5.077 | 182.3 | 0.8891 | 0.9714 |
| 10 | 0.01696 | 34.84 | 85.08 | 0.8856 | 0.9716 |
| 11 | 0.1569 | 33.13 | 190.3 | 0.9958 | 0.9716 |
| 12 | 0.03718 | 5.464 | 248.7 | 0.9449 | 0.9702 |
| 13 | 0.01949 | 15.39 | 49.39 | 0.1021 | 0.9593 |
| 14 | 0.6047 | 11.07 | 106.3 | 0.1091 | 0.9693 |
| 15 | 0.1576 | 5.25 | 297.3 | 0.1108 | 0.9696 |

| | | | | | |
|---|---|---|---|---|---|
| 16 | 0.2196 | 5.658 | 164.4 | 0.9158 | 0.9741 |
| 17 | 0.01259 | 5.12 | 233.7 | 0.6258 | 0.9768 |
| 18 | 0.599 | 8.632 | 231.4 | 0.4695 | 0.9696 |
| 19 | 0.03539 | 5.213 | 84.0 | 0.7726 | 0.9744 |
| 20 | 0.2311 | 5.181 | 238.0 | 0.4045 | 0.9721 |
| 21 | 0.001677 | 34.75 | 57.33 | 0.1706 | 0.9423 |
| 22 | 0.07261 | 34.78 | 144.2 | 0.4977 | 0.9711 |
| 23 | 0.05849 | 32.9 | 279.4 | 0.9094 | 0.9752 |
| 24 | 0.000612 | 5.583 | 209.8 | 0.8951 | 0.942 |
| 25 | 0.9515 | 34.84 | 248.8 | 0.6843 | 0.9669 |
| 26 | 0.9829 | 19.12 | 28.74 | 0.8571 | 0.9689 |
| 27 | 0.886 | 32.38 | 275.3 | 0.9044 | 0.9683 |
| 28 | 0.6127 | 5.323 | 184.3 | 0.2443 | 0.9695 |
| 29 | 0.9562 | 5.484 | 138.5 | 0.6459 | 0.9669 |
| 30 | 0.836 | 5.308 | 31.64 | 0.05296 | 0.9667 |
| 31 | 0.1133 | 15.74 | 294.1 | 0.9701 | 0.9708 |
| 32 | 0.9233 | 22.01 | 154.3 | 0.9929 | 0.9685 |
| 33 | 0.9996 | 34.8 | 124.9 | 0.8693 | 0.9685 |
| 34 | 0.9612 | 34.91 | 157.2 | 0.92 | 0.9688 |
| 35 | 0.08564 | 21.82 | 10.02 | 0.01642 | 0.9477 |
| 36 | 0.6485 | 34.81 | 29.24 | 0.06077 | 0.9692 |
| 37 | 0.9735 | 21.55 | 79.4 | 0.7765 | 0.9672 |
| 38 | 0.8287 | 6.332 | 286.3 | 0.8931 | 0.9698 |
| 39 | 0.1454 | 8.875 | 235.9 | 0.2883 | 0.9713 |
| 40 | 0.2336 | 21.64 | 242.7 | 0.9865 | 0.9739 |
| 41 | 0.8836 | 5.425 | 70.31 | 0.0631 | 0.9672 |
| 42 | 0.02863 | 34.14 | 86.71 | 0.9099 | 0.9731 |
| 43 | 0.3259 | 12.69 | 191.3 | 0.9835 | 0.9722 |
| 44 | 0.009779 | 20.77 | 92.33 | 0.8829 | 0.9637 |
| 45 | 0.04701 | 20.91 | 271.4 | 0.9828 | 0.9708 |
| **46** | **0.02381** | **6.919** | **299.5** | **0.9287** | **0.9791** |
| 47 | 0.01089 | 5.964 | 24.25 | 0.9974 | 0.9392 |
| 48 | 0.939 | 16.1 | 46.05 | 0.03474 | 0.9671 |
| 49 | 0.9566 | 6.149 | 92.66 | 0.9749 | 0.9687 |
| 50 | 0.8834 | 5.04 | 43.08 | 0.785 | 0.9684 |
| 51 | 0.9345 | 33.79 | 19.72 | 0.1153 | 0.9671 |
| 52 | 0.5599 | 34.34 | 209.2 | 0.9586 | 0.9707 |
| 53 | 0.04613 | 5.274 | 150.2 | 0.9913 | 0.9767 |

TABLE III THE PERFORMANCE OF THE PROPOSED METHOD WHEN TRAINED ON THE CELEBDF-FACEFORENCICS++ (C23) SET AND EVALUATED ON THE CELEBDF TEST SET AND DEEPFAKETIMIT TESTING SETS

| DATASET | ACCURACY | Recall | Precision | F-measure | Specificity | Sensitivity | AUROC |
|---|---|---|---|---|---|---|---|
| CELEBDF | **%**97.88 | %97.68 | %99.12 | %98.39 | %98.27 | %97.68 | %97.65 |
| DeepfakeTIMIT | %98.44 | %98.12 | %98.74 | %98.43 | %98.75 | %98.12 | %98.44 |

TABLE IV THE AUROC VALIDATION SCORE FOR EACH HYPERPARAMETER COMBINATION ON THE FAKEAVCELEB VISUAL VIDEOS DATASET

| **ITERATION** | **learning_rate** | **max_depth** | **n_estimators** | **reg_alpha** | **AUROC score** |
|---|---|---|---|---|---|
| 1 | 0.3751 | 24.21 | 285.5 | 0.07568 | 0.9874 |
| 2 | 0.7769 | 29.98 | 25.89 | 0.8177 | 0.9892 |
| 3 | 0.8854 | 26.67 | 10.74 | 0.9812 | 0.9835 |
| **4** | **0.2503** | **5.005** | **151.1** | **0.1215** | **0.9925** |
| 5 | 0.5979 | 34.99 | 181.7 | 0.749 | 0.988 |
| 6 | 0.7081 | 8.501 | 154.2 | 0.7557 | 0.9884 |
| 7 | 0.7139 | 5.133 | 146.5 | 0.08625 | 0.9823 |
| 8 | 0.3834 | 5.028 | 244.0 | 0.1609 | 0.9877 |
| 9 | 0.1924 | 5.96 | 299.9 | 0.5826 | 0.986 |
| 10 | 0.1453 | 5.599 | 34.12 | 0.07629 | 0.9871 |
| 11 | 0.1671 | 5.015 | 195.4 | 0.7694 | 0.9868 |
| 12 | 0.663 | 25.8 | 23.12 | 0.03216 | 0.989 |
| 13 | 0.1033 | 34.5 | 88.01 | 0.418 | 0.991 |

TABLE V THE PERFORMANCE OF THE PROPOSED METHOD WHEN TRAINED ON THE FAKEAVCELEB VISUAL VIDEOS DATASET

| ACCURACY | Recall | Precision | F-measure | Specificity | Sensitivity | AUROC |
|---|---|---|---|---|---|---|
| %99.50 | %100 | %98.97 | %99.48 | %99.06 | %100 | %99.21 |
| | | | | | | |

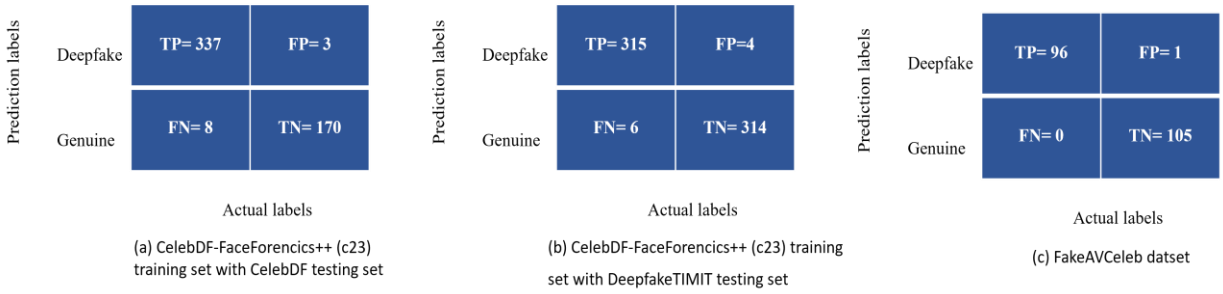



Fig. 4. The confusion matrix visualization of the proposed method on CelebDF-FaceForencics++ (c23) training set with CelebDF and DeepfakeTIMIT testing sets, and FakeAVCeleb visual videos dataset.

Fig. 6 compares the proposed deepfake video detection method with current state-of-the-art methods [10], [26], [53], [70], [74] using evaluation metrics on CelebDF-FaceForencics++ (c23) and FakeAVCeleb visual video datasets. As can be seen in Fig. 6, the proposed method has achieved higher performance as compared to the current methods. The experiments are performed on an OMEN HP laptop running Windows 11, an Intel (R) Core (TM) i7-9750H processor, and a 6-gigabyte RTX 2060 GPU. Python programming language is used to implement the proposed method. The implementation makes use of Python modules including keras, sklearn, openCV, matplotlib, os, random, tensorflow, numpy, xgboost and bayes_opt.

It can be concluded that employing the Mask R-CNN and selecting the optimal bounding box for face detection from video frames helped to reveal more artifacts. This improved the overall performance of the proposed deepfake video detection method. Additionally, a meaningful spatial representation of the detected faces was produced using the proposed improved version of the Xception-Network. This played an important role in differentiating between genuine and deepfake videos. Furthermore, using XGBoost with the BO algorithm on top of extracted representation produced optimal hyperparameters that prevent overfitting and improved the deepfake detection method performance by producing more precise predictions.

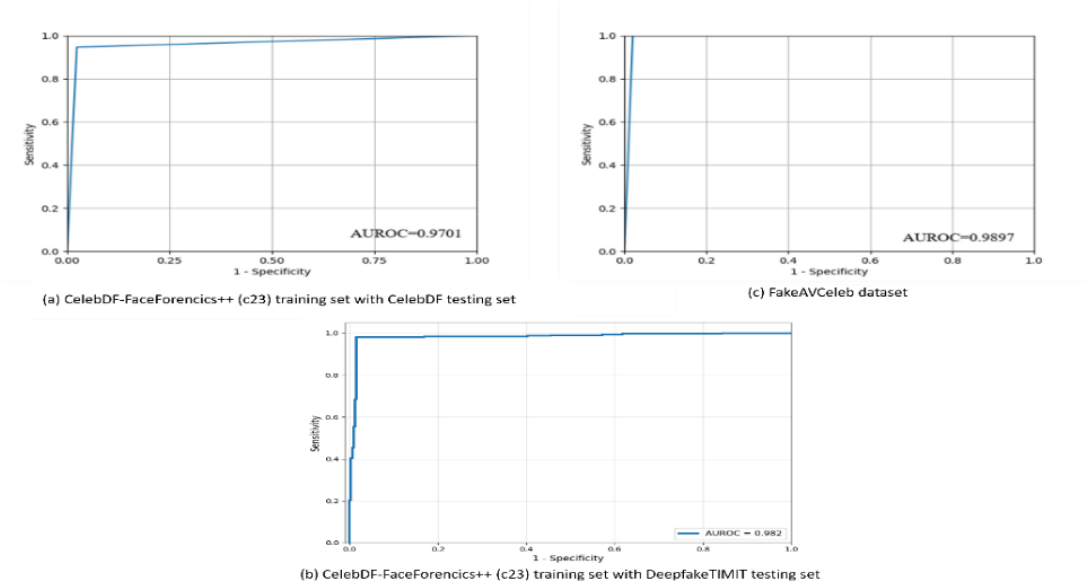
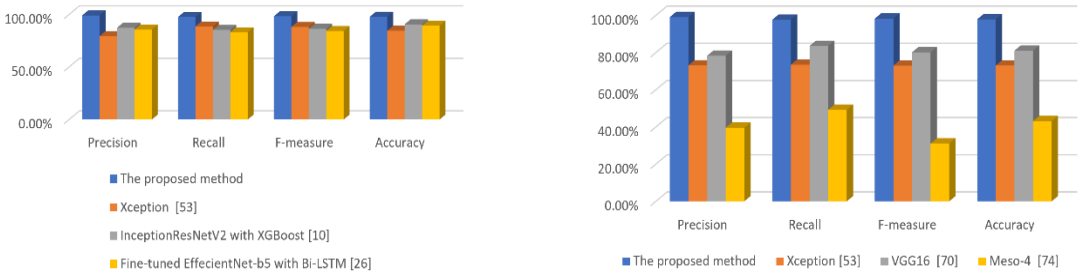



Fig. 5. The ROC curve and the AUROC curve metric of the proposed method on CelebDF-FaceForencics++ (c23) training set with CelebDF and DeepfakeTIMIT testing sets, and FakeAVCeleb visual videos dataset.




(a) CelebDF-FaceForencies++ (c23) training dataset, and CelebDF testing set

(b) FakeAVCeleb

Fig. 6. The evaluation metrics of the proposed method for deepfake video detection compared to current state-of-the-art methods.

## V. Conclusion and Future Work

A new methodology for detecting deepfake videos has been introduced. It seeks to discover artifacts and visual discrepancies from video and then determine its authenticity. The Mask R-CNN is utilized to detect human faces from video frames. The optimal bounding box representing the facial area per frame is then chosen to find more artifacts which assists in ameliorating the method performance. An improved version of the Xception-Network is employed to produce an instructive spatial representation of face frames. It helps to distinguish between genuine and fake videos. The XGBoost with the Bayesian Optimization (BO) algorithm is applied to the extracted representation to decide video authenticity. The BO algorithm produced optimal hyperparameters of the XGBoost which assists in preventing overfitting. This provides more accurate predictions and ameliorates the overall performance of the proposed deepfake video detection method. CelebDF-FaceForencics++ (c23) and FakeAVCeleb visual videos datasets have been employed to train and validate the proposed method. CelebDF, DeepfakeTIMIT, and FakeAVCeleb datasets have been employed to test the proposed method. The proposed method achieved %97.88 accuracy, %97.68 recall, %99.12 precision, %98.27 F-measure, %98.27 specificity, %97.68 sensitivity, and %97.65 AUROC on the trained CelebDF-FaceForencics++ (c23) and tested CelebDF datasets. Additionally, it yielded %98.44 accuracy, %98.12 recall, %98.74 precision, %98.43 F-measure, %98.75 specificity, %98.12 sensitivity, and %98.44 AUROC on the trained CelebDF-FaceForencics++ (c23) and tested DeepfakeTIMIT datasets. Moreover, it yielded %99.50 accuracy, %100 recall, %98.97 precision, %99.48 F-measure, %99.06 specificity, %100 sensitivity, and %99.21 AUROC on the FakeAVCeleb visual dataset. As a result, the proposed method effectively outperformed the current state-of-the-art methods.

As the volume of fake content is continuously growing, there is a need to keep up by ameliorating the current deepfake detection methods to be able to detect the fakes produced by various manipulation methods. This could be accomplished using various augmentation techniques, other optimization algorithms, and more developed architectures. Additionally, there is a need to create a huge video dataset that resembles those circulating Online in an attempt to improve the generalization ability of the detection methods.

## Conflict of Interest

The authors declare no conflict of interest.

## Data Availability

The FakeAVCeleb dataset is available from the FakeAVCeleb site:

https://github.com/DASH-Lab/FakeAVCeleb.

The FaceForencies++ dataset is available from the FaceForensics site:

https://github.com/ondyari/FaceForensics.

The Celeb-DF dataset is available from the celeb-deepfakeforensics site:

https://github.com/yuezunli/celeb-deepfakeforensics.

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# Enhancing Usability and Cognitive Engagement in Elderly Products Through Brain-Computer Interface Technologies

Daijiao Shi*, Chao Jiang, Chenhan Huang
School of Arts, Anhui University of Finance and Economics, Bengbu 233030, China

***Abstract*—This study addresses the limitations of traditional elderly care products in terms of intelligence and user experience by integrating human-computer interaction (HCI) principles into a product design framework for the elderly. This study explores the importance of feature extraction in human-computer interaction systems, emphasizes its key role in enhancing user adaptability and interaction efficiency, and deeply analyzes its impact on brain-computer interface (BCI) technology. At the same time, the study conducts simulation experiments to evaluate the effectiveness of various algorithms in processing two types of motor imagery tasks. Finally, the obtained results provide a comparative evaluation of the algorithms and highlight their respective strengths and limitations.**

***Keywords*—Big data; human-computer interaction; the elderly; product design**

## I. INTRODUCTION

The opening of the digital age has brought about rapid changes in the entire human society. For the elderly, the most fundamental change compared to the past is not the decline of their own physical and psychological functions, but the disappearance of the polar opposite ways of thinking they once used to understand the world, which accelerates their loss in modern society. This "lost" is precisely the uncertainty caused by the complexity and constant movement changes at the intersection of the current digital and aging society, the movement process of social development and the aging process of the elderly [1], the uncertainty across age and culture as opposed to precision, and the interpenetration of the overall and local relationships between the society as a whole and the aging population, elderly groups. Its basic spirit is to oppose the binary assertion of "either or that" in classical logic, and to recognize the fuzzy state of the existence of "this or that" between things. Moreover, it focuses on treating the ambiguity between things as a whole, and processing them to eliminate the ambiguity [2]. At present, the technology, culture, experience and other elements of the products used by the elderly are becoming more and more complex, and the consumption concept, cognitive ability and aesthetic awareness of the elderly are also changing. While they show some similarities, there has been a gradual shift from a group style to an unpredictable individualistic style. Understanding and viewing the uncertainty of thinking and thinking of the elderly from the perspective of fuzzy theory, the fusion of new and old ideas, and the multiple symbiosis become the rationalization of the overall needs of the elderly, is a necessary supplement to the humane care for the elderly [3].

With the progress of social civilization, digital products gradually tend to focus on humanized and personalized design in the process of design exploration. The commonality and individuality of the elderly are dialectically unified and interpenetrating, which is mainly reflected in their universal commonality, that is, the basic requirements for the function, safety and interaction of products, but they also have their own individuality, that is, their character, ability, emotional and aesthetic specificity. In the process of designing digital interactive products, it is necessary to start from the commonness and personality of the elderly. First, it is necessary to consider the commonness of the elderly contained in their personality, and reflect the cultural diversity and people-oriented thinking of products in a personalized way. Secondly, in the commonness on this basis, it is necessary to humanize the personality of the elderly in a flexible way, so as to reflect the humanistic care and emotional respect of the products, and enable the elderly to meet their individual needs in the commonness of the products. From the perspective of the vague demands of the elderly, it is necessary to emphasize the use of holistic and dialectical, common and individual, universal and special ways to understand people, explain products and solve problems in digital interactive products for the elderly, and integrate them into product design. The relationship between the elderly and digital interaction is full of flexible features.

In the design research of digital interactive products, emotional communication and interaction design are inseparable, so the emotional experience between interactive products and the elderly is particularly important. Nowadays, interactive design products for the elderly should not only meet the functional needs, but should stimulate their positive emotions and establish an emotional connection between the products and the elderly. The emotions of the elderly have become stable and complex through the development of society and the precipitation of time. In this case, there may be positive emotions such as joy, happiness, etc., and negative emotions such as disappointment may appear, sadness, loneliness, etc. With the continuous maturity of today's digital technology, interactive products for the elderly, on the basis of technical support, have begun to slowly seek the fuzzy appeals of the elderly's emotions. Meanwhile, technology allows the

elderly to have a strong emotional resonance while enjoying high-tech and intelligent interaction, so as to maximize the positive emotions of the elderly and eliminate the sensitivity and anxiety brought by social development.

The purpose of this article is to improve the intelligence and reliability of elderly product design, solve the problems of inconvenient interaction and insufficient intelligence in traditional elderly products, enhance the emergency response capability of elderly products in emergency situations, and improve the multi-source information fusion effect of elderly products.

This study addresses the limitations of traditional elderly care products in terms of intelligence and user experience by integrating human-computer interaction (HCI) principles into a product design framework for the elderly. Moreover, this study explores the importance of feature extraction in HCI systems and emphasizes its key role in enhancing user adaptability and interaction efficiency.

This paper integrates human-computer interaction (HCI) concepts to analyze the product design system for the elderly, aiming to enhance user experience and service effectiveness. First, the introduction discusses the background, significance, and objectives of elderly care products, while the related work section reviews the current state of such products and the integration of intelligent technologies. Secondly, the algorithm section presents the development and integration of algorithms into the proposed model, followed by the experimental section, where the constructed model is evaluated through experiments, and the results are analyzed and discussed. Finally, the conclusion summarizes the study's key contributions and provides insights for future research directions.

## II. Related Work

The design of elderly products needs to meet the living needs of the elderly, while also having certain emergency functions that can achieve real-time interaction with the elderly. Next, we will analyze the design needs of elderly products and the current research status of their intelligence.

### *A. Elderly Interactive Product Experience Needs*

Form and function are the basic elements for the existence of products, but with the advent of diversification, digitization, and non-material society, the synergistic relationship between the "old-fashioned" in form and the "support for the elderly" in function of elderly products has been synergistic in the past, and is heading for an indeterminate demise. The rapid development of material technology and the emotional scarcity of the elderly make the relationship between the morphological, semantic and functional development of elderly products constantly changing. Especially, for the elderly products in the digital form, their form has long been beyond the shackles of function, showing a flat and homogeneous trend [4]. The functional definition of elderly products has gradually expanded from a single use category such as "helping the elderly", and "entertaining the elderly" to the cultural functions, aesthetic functions, social functions, emotional functions and other fields of high-level needs of the elderly. So far, the form of the product function for the elderly and the function of the form are interdependent, and its conceptual definition and relationship development have shown a vague and uncertain state in the movement change [5].

Before retirement, the elderly showed positive and progressive functional social roles as unit leaders or staff. After retirement, they take on the role of taking care of the family as grandchildren and grandparents of parents, including the superposition and transformation of roles such as patients, and their original social roles are gradually replaced by emotional roles. Moreover, as they grow older, their explicit behaviors become more diverse due to changes in the content and nature of their roles. The nature and complexity of elderly products will eventually generate multiple demands on the functions, forms, interactions, emotions, etc. of elderly products [6]. It is undoubtedly difficult to accurately describe the diverse needs of the elderly at different stages. However, if people can dialectically connect the causal thinking of the elderly's role transformation from a holistic rather than a partial perspective, so that the contours of the environment, culture, form, color and other parts related to elderly products disappear in the ever-increasing interconnection and re-form a unified whole, it will undoubtedly be easier for people to accurately define the conceptual attributes of elderly products and expand new innovation horizons [7].

The cognitive, behavioral, cultural, and psychological characteristics of the elderly are no longer simply personal attributes, but are more likely to become a component of a product. Products are no longer just "products" in the traditional sense, but must rely on basic conditions such as the elderly's interactive behaviors, physiological and psychological characteristics. The mutual penetration of advantages and applications between the elderly and products, and the complementarity of disadvantages, will form a new development form of elderly products [8]. The "interpenetration" between the elderly and the product makes the design focus shift from focusing on the function of "material objects" to the elderly's own participation and creation. Such products are open to the elderly, and are also very "Self-conscious" and "Conceptual". The interpenetration characteristics of elderly users and products can undoubtedly provide more personalized humanistic care for the elderly [9].

The functional diversity of digital products means that their functions are not unique, and they do not deliberately highlight or emphasize what the product can do. Simply put, it can basically meet the needs of life without considering the particularity of other users. With the development of society, economy and culture, the emotional and artistic expressions of the elderly in their later years have gradually enriched, and the need for basic living security has gradually transitioned to spiritual and cultural life sustenance [10]. In response to this artistic ambiguity in life, it is considered to give the elderly a higher spiritual level from an artistic perspective, add artistic design to interactive products for the elderly, make the products more humane and emotional, and to a certain extent eliminate the tension and indifference brought to them by digital products [11]. By integrating modern life concepts, namely the art of living, into elderly products, digital elderly products can be made inseparable from the daily lives of the elderly. On the basis of interactivity, the most appealing artistic means can be used to enhance the value and art of elderly

products and the lives of the elderly. In addition, penetration and overlap can enable the elderly to realize an artistic life and resolve their ambiguous artistic demands [12].

### B. Big Data and the Interaction Needs of the Elderly

Reference [13] suggested that the layout and design of health information websites need to be fully considered to meet the search and acquisition of health information by the elderly population. Reference [14] suggested that the use of online health information tools by the elderly can greatly improve the efficiency of health information communication and exchange among the elderly. At the same time, it can further enhance the level of self-care. According to [15], computer course training for the elderly can effectively reduce anxiety and improve self-identification, which is very helpful for the elderly to search for health information through the Internet. Reference [16] found through observation experiments on nearly 20 elderly people that they are not particularly skilled in constructing and modifying search formulas and keywords during information search, and are not particularly familiar with the use of different search tools, browsers, etc. In addition, elderly people also lack relevant knowledge and experience in judging the authenticity of online health information. Reference [17] conducted a questionnaire survey on more than 400 elderly people through the Internet. The content of the survey is the health information search behavior of elderly people using Internet channels. The research results show that demographic factors, subjective attitudes and other factors will have a significant impact on the health information search behavior of elderly people. Reference [18] suggested that some elderly people with computer operation experience will be more flexible in constructing, modifying search equations, and selecting appropriate search terms to achieve the goal of searching for health information. Reference [19] suggested that compared to the elderly population who have not received a good education and have a lower level of education, those with higher education and better education tend to easily search for and obtain the online health information they need.

Overall, the research status is shown in Table I:

TABLE I. SUMMARY OF RELATED WORK

| Research contents | Related work |
|---|---|
| Elderly product demand | Digitization |
| | Function, form, interaction, emotion |
| | Environment, culture, form, color |
| | Interactive behavior, physiological and psychological characteristics |
| | The artistic quality of the product |
| | Humanization and Emotion |
| Intelligent products for the elderly | Information communication and exchange |
| | Self care |
| | Reduce anxiety and enhance self-identity |
| | Search for health information |
| | Intelligent emergency response |

## III. METHODOLOGY

### A. Event-Related Synchronization / Desynchronization (ERS/ERD) Phenomenon

In human-computer communication operation, there are mainly two types of errors: cognitive errors and subconscious errors. (1) Cognitive errors are often the lack of people's cognitive ability and cognitive degree, which is a type of error caused by people's knowledge ability failing to meet the needs of product use. For example, when people use a new lock, they often try several times to open it with the key. Moreover, cognitive errors are often unexpected errors, which are related to the user's early cognition and learning ability of the product. However, designers can reduce the probability of cognitive errors through reasonable guidance and prompts in product design. (2) Subconsciousness is defined in psychology as people's unconscious behavior tendency, and subconsciousness refers to unconscious and unconscious psychological activities. Unconscious errors are also inadvertently generated. They are the user's involuntary operation errors under the guidance of common sense cognition.

The aging of the elderly leads to the aging of the metabolism and organ functions of the elderly to varying degrees, and also leads to a large gap between their physical condition and learning ability and the young and middle-aged people in their prime of life, making the elderly more likely to make mistakes in one way or another when using products. Based on the physiological conditions of the elderly, the analysis of the fault tolerance elements of the elderly group can understand the error prone rules of the elderly when using products, so that the fault tolerance design for the elderly group is more targeted. There are two aspects of decline in the physiological function of the elderly: (1) decreased sensory ability. It is mainly reflected in the decline of the five senses, and the resulting decline in the perception of things. For example, color weakness, cataracts, glaucoma and other problems caused by visual deterioration are also the main inducements for the elderly to make mistakes when using the product. Visual deterioration leads to their poor understanding of functional zoning, prompt signs, button layout and other aspects of the product when using the product, which is prone to operational errors or improper use. The decline of hearing ability makes the voice of the elderly very sensitive. At the same time, the voice below the hearing threshold is likely to lead to cognitive or subconscious errors in operation due to the inability of the elderly to hear, while the voice above the hearing threshold or sharp and harsh sound will frighten the elderly. In addition, the decline of the sense of smell, taste and touch of the elderly will reduce their perception of the outside world, which is easy to cause scald, frostbite and other problems when using the product. (2) Decreased behavioral ability. It is mainly reflected in the decline of action ability and cognitive ability. Compared with young people, the elderly usually have problems such as deterioration of human quality, slowness of movement and decline of physical strength, which makes them prone to some unintentional mistakes. For example, the old mercury column sphygmomanometer needs to press the air bag vigorously to obtain a measurement data. The elderly's ability to move decreases, resulting in insufficient pressing force, which is likely to lead to deviation errors in the

measurement results. On the other hand, aging physical functions of the elderly are prone to slow reaction and cognitive decline. At the same time, due to the relatively closed life of the elderly, it is also easy to have a sense of emptiness and reject new things. This has led to the decline of the learning ability and adaptability of the elderly when they are exposed to new products, resulting in boredom and rejection of new products. For example, the product does not work due to incorrect operation due to unclear understanding of the product's instructions, or gives up the operation due to impatience with the use of the product.

Event-related synchronization/desynchronization can be used to analyze and distinguish different motor imagery EEG signals to control the motion control system of the robot.

When the cerebral cortex is stimulated by endogenous or exogenous events, it induces changes in the physiological state of some functional areas, resulting in changes in the rhythm of certain brain wave frequency bands. The energy of the frequency band in the cerebral cortex is reduced, and the brain has a brief pause.

The formula for calculating ERS/ERD (Event related synchronization/desynchronization) is [20]:

$$ERD = \frac{A - R}{R} \times 100\% \tag{1}$$

In the above formula, R represents the power of a specific frequency band in the training signal, and A represents the power of a specific frequency band in the test signal.

### B. Feature Extraction of EEG (Electroencephalogram) Signals

The average energy extracted in the 8-16Hz frequency band is calculated by the following formula [21]:

$$P = \frac{1}{N}\sum_{i=1}^{N} x^2 \tag{2}$$

In the above formula, N represents the number of extracted frequency band data in each group, x represents the extracted 8-16Hz frequency band data, and P represents the average energy of 140 extracted frequency bands.

It is suitable for feature extraction for binary classification tasks. Fig. 1 shows the CSP algorithm flow.

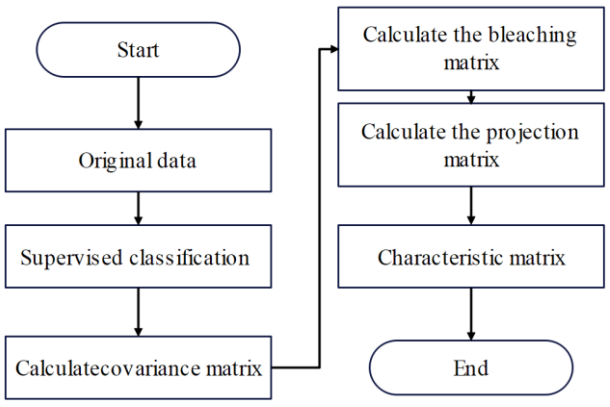



Fig. 1. Flow of the co-space pattern.

The process of CSP is explained as follows:

*1)* The algorithm classifies the raw data according to categories. Two types of sample data E can be classified into $E_1$ and $E_2$. $E_1$ is the first type of sample data, and $E_2$ is the second type of sample data.

*2)* The algorithm calculates the covariance matrix of the segmented original data, and the calculation formula of the covariance matrix is:

$$C_i = \frac{E_i \cdot E_i^T}{trace\left(E_i \cdot E_i^T\right)}, (i = 1,2) \tag{3}$$

$trace(E)$ means to find the trace of matrix E.

The algorithm calculates the covariance matrix of the classified raw data separately. $C_C$ is the sum of the spatial covariance matrices of the two types of data, then there are:

$$C_C = C_1 + C_2 \tag{4}$$

*3)* The algorithm performs orthogonal whitening transformation and simultaneous diagonalization, where $C_C$ is a positive definite matrix, and according to the singular value decomposition theorem:

$$C_C = U_C \Lambda_C U_C^T \tag{5}$$

$U_C$ is the eigenvector matrix, $\Lambda_C$ represents the diagonal matrix of eigenvalues, and the eigenvalues are arranged in descending order. By whitening transformation $U_C$, it can be obtained:

$$P = \frac{1}{\sqrt{\Lambda_C}} \cdot U_C^T \tag{6}$$

For $U_C^T$, the corresponding eigenvector matrix after the eigenvalues are in descending order should also be sorted in descending order, and when the matrix P is applied to $C_1$ and $C_2$, it can be obtained:

$$\begin{cases} S_1 = PC_1P^T \\ S_2 = PC_2P^T \end{cases} \tag{7}$$

$S_1$ and $S_2$ have common eigenvectors:

$$\begin{cases} S_1 = B\Lambda_1 B^T \\ S_2 = B\Lambda_2 B^T \end{cases} \tag{8}$$

$$\Lambda_1 + \Lambda_2 = I \tag{9}$$

Among them, I is the identity matrix. From it, it can be seen that the sum of the eigenvalues of $S_1$ and $S_2$ is equal to 1.

*4)* The algorithm computes the projection matrix.

The classification of two types of problems can be realized by using the matrix Q, and the projection matrix can be obtained:

$$W = \left(Q^T P\right)^T \tag{10}$$

*5)* The algorithm obtains the feature matrix through projection.

$$Z_{M\times N} = W_{M\times N} \tag{11}$$

*6)* Features are normalized.

$$y_i = \frac{log\left(var\left(Z_i\right)\right)}{\sum_{n=1}^{2m} var\left(z_n\right)} \tag{12}$$

Among them, $y_i$ is the normalized feature matrix of the i-th sample.

The obtained feature matrix is normalized to obtain the feature vectors $F_l$ and $F_r$ of the left and right motor imagery EEG signals.

$$\begin{cases} F_l = \left[v_1^l, v_2^l, ..., v_j^l, ...v_{2m}^l,\right] \\ F_r = \left[v_1^r, v_2^r, ..., v_j^r, ...v_{2m}^r,\right] \end{cases} \tag{13}$$

In order to maximize the recognition accuracy in classification and recognition, usually when m=2, the data of the first m rows and the last m rows are selected as the optimal feature vectors.

In general, The AR model can be represented as [22]:

$$x(n) = -\sum_{i=1}^{p} a_i x(n-i) + \mu(n) \tag{14}$$

Among them,

$$\mu(n) = \sum_{k=0}^{q} b_k w(n-k) \tag{15}$$

Both sides of Formula (14) are simultaneously multiplied by x(n+m), x(n) autocorrelation function.

$$R_x(x) = \begin{cases} -\sum_{i=1}^{p} a_i R_x(m-i), m>0 \\ -\sum_{i=1}^{p} a_i R_x(m-i) + \sigma^2, m=0 \end{cases} \tag{16}$$

By substituting Formula (15) into Formula (14) and performing Z transform,

$$\sum_{i=0}^{p} a_i X(z) z^{-i} = \sum_{k=0}^{q} b_k X(z) z^{-k} \tag{17}$$

We set:

$$\begin{cases} \sum_{i=0}^{p} a_i X(z) z^{-i} = A(Z) \\ \sum_{k=0}^{q} b_k X(z) z^{-k} = B(Z) \end{cases} \tag{18}$$

## IV. Model Design and Validation

### A. Experimental Environment and Methods

Traditional digital interactive products often give people a sense of technology and indifference. In particular, for the elderly with physical decline and inner sensitivity, these digital products cannot make them feel comfortable and pleasant to use, but will aggravate their inner anxiety to a certain extent and have a bad impact. Therefore, it is necessary to take advantage of the ambiguity characteristics of interactive products, add the characteristics of the perspective of the elderly, and use flexible processing to transform traditional digital interactive products into a product form that the elderly is happy to accept. Moreover, digital interactive products for the elderly need to subvert the traditional concept. Behind the improvement of the overall function, the design concept of people-oriented and flexible emotions is integrated to obtain the recognition of the elderly, so as to give the elderly more care and care. Fig. 2 is an analysis diagram of the design concept of this product. Behind it is an ecological chain service that cares for the elderly in a multi-faceted and humanized manner. Through online surveys, it is found that most elderly people worry that those “weird-looking devices” will make other elderly people feel “that they are unable to take care of themselves”. Therefore, the appearance design of digital interactive products must fully consider the psychological and emotional reactions of the elderly.

The simulation model in this article includes a nursing module, a motion control module, and a vital sign information detection module. The intelligent interactive terminal motion adopts a DC servo motor, which can not only withstand high load operation, but also has high operating accuracy. If conditions permit, it can be equipped with a high-performance main control chip. The nursing function of intelligent interactive terminals mainly includes cleaning and caring for urine and feces, including processes such as cleaning the spray bar, extending and closing it with warm water, and drying it with warm air. The human vital sign monitoring function of intelligent interactive terminals real-time transmits the human vital sign parameters collected by sensors, such as temperature, heart rate, etc., to the human-computer interaction interface, or through the establishment of a wireless local area network, enables family members or nursing staff to monitor the patient's physical condition in real time.

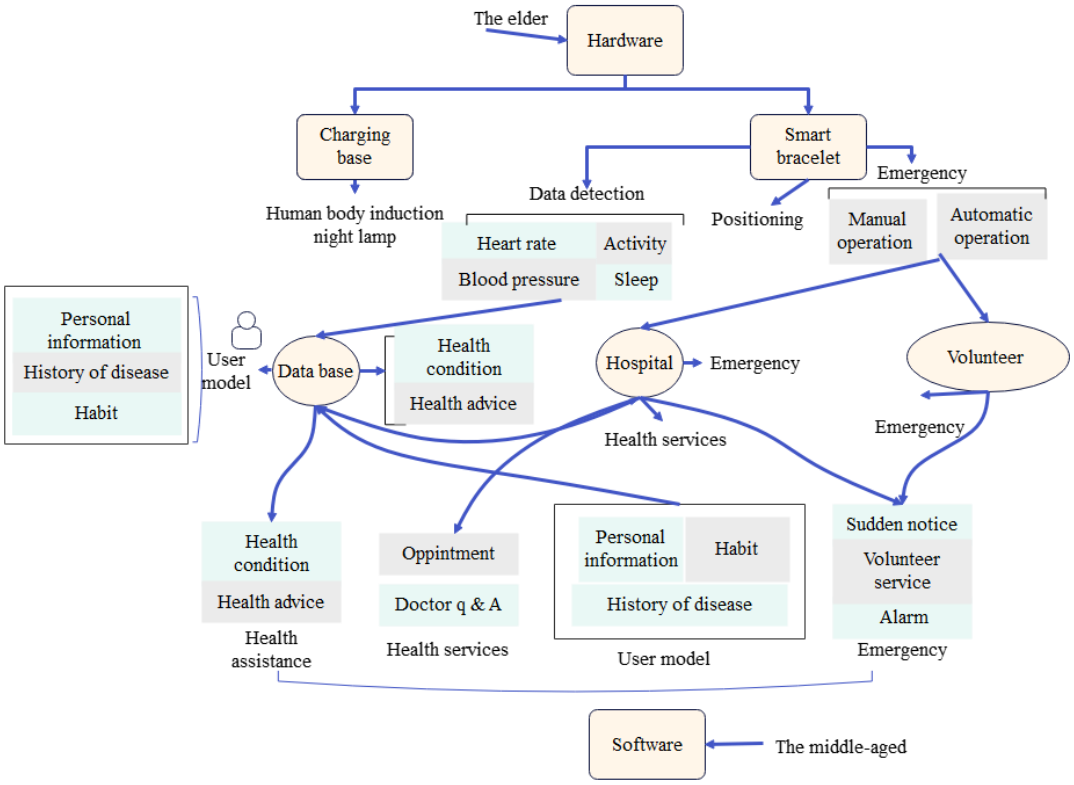


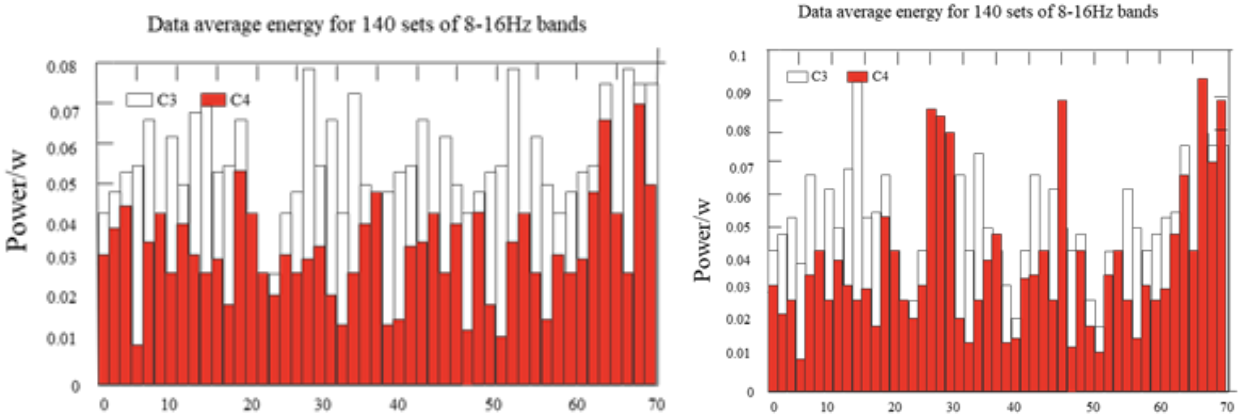

Fig. 2. Analysis diagram of the design concept.

Due to the limitations of the laboratory environment, EEG data is collected and recorded in a designated environment and sent to a computer through the BCI interface. The EEG signal preprocessing, feature extraction, and classification recognition algorithms are developed using MATLAB R2018a software for processing. Then, this paper uses VC++ language to write the module program and adds the MATLAB R2018a calling engine so that the module program can call MATLAB R2018a to process data and send it to the main controller through the wireless communication module to control the interactive terminal. Therefore, for the processing of collected EEG data, the laboratory currently uses an offline BCI system to record and save EEG data in real time. The collected EEG signals are wirelessly transmitted to a computer and preprocessed, feature extracted, and classified using MATLAB pre-programmed processing algorithms.

The default setting of the model in this article is the elderly mode, which is verified by nursing staff or family members and granted system data access permission. The data in this article cannot be uploaded to online platforms by default. To obtain the data in this article's model, the user's own verification and consent are required, making it more reliable in protecting the user's personal privacy.

### B. Test Results

The Energy simulation (Example 1) and DWT feature extraction are shown in Fig. 3 and Fig. 4.




(a) Imagination of the left-hand movement

(a) Imagination of the right hand movement

Fig. 3. Energy simulation example 1.

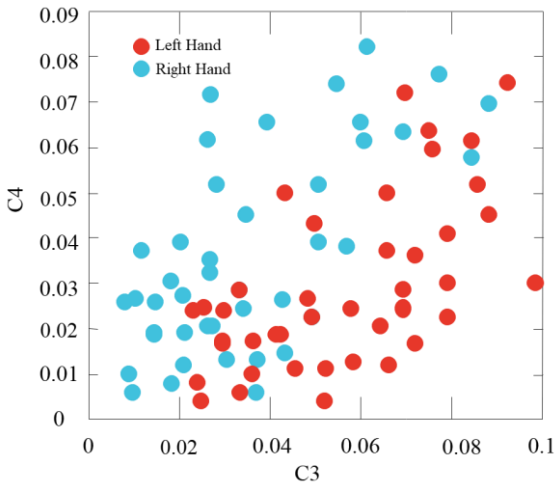
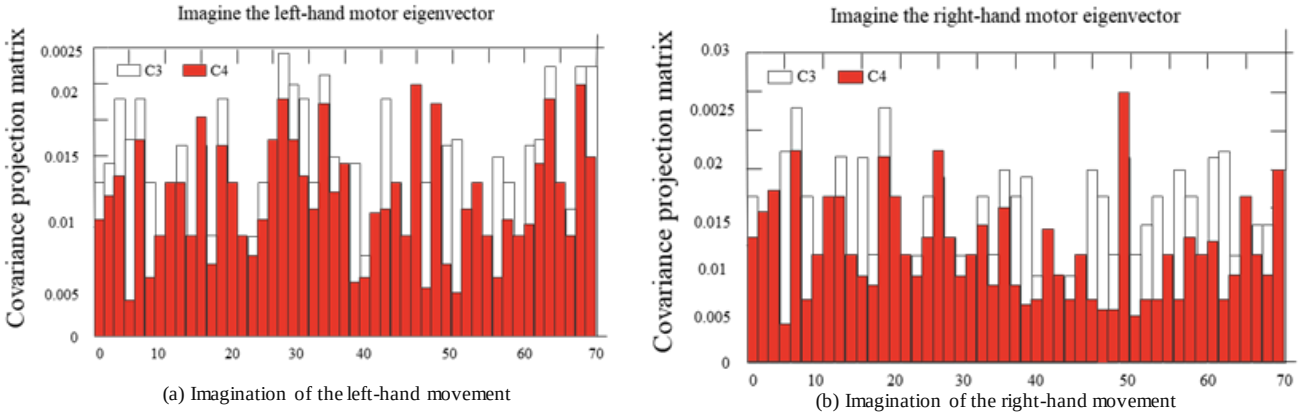



Fig. 4. DWT feature extraction.

Since CSP is used alone to extract EEG features and seriously lacks feature information in the time and frequency domains, the feature vector obtained by feature processing will have defects. Firstly, the EEG signal is decomposed into the EEG frequency bands of ERS/ERD phenomenon containing alpha wave and mu rhythm by DWT. Then, the extracted frequency bands are extracted by CSP, as shown in Fig. 5 and Fig. 6.

As shown in Fig. 7 and 8, the model has been validated to have good convergence through data.

Fig. 9 is the Feature extraction of AR model. Usually, energy simulation example 4 is shown in Fig. 10.




(a) Imagination of the left-hand movement

(b) Imagination of the right-hand movement

Fig. 5. Energy simulation example 2.

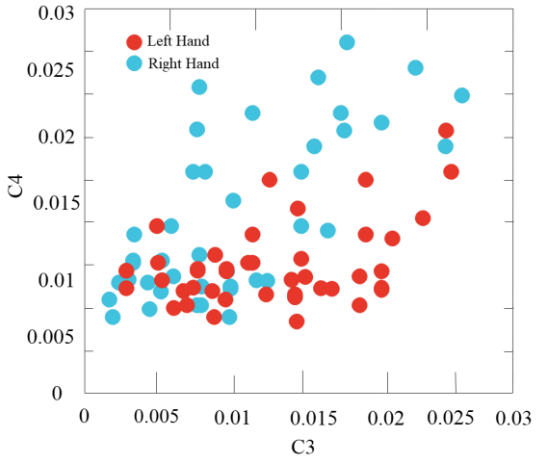
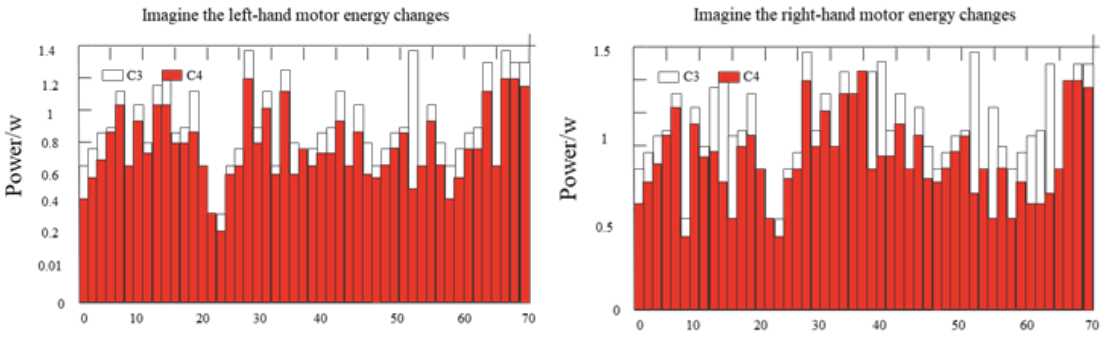



Fig. 6. CSP Feature extraction.




(a) Imagination of the left-hand movement (b) Imagination of the right-hand movement

Fig. 7. Energy simulation example 3.

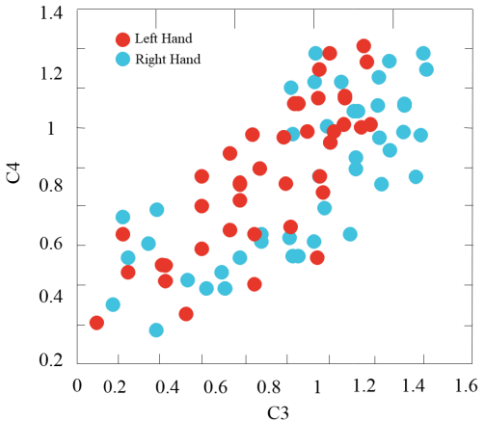
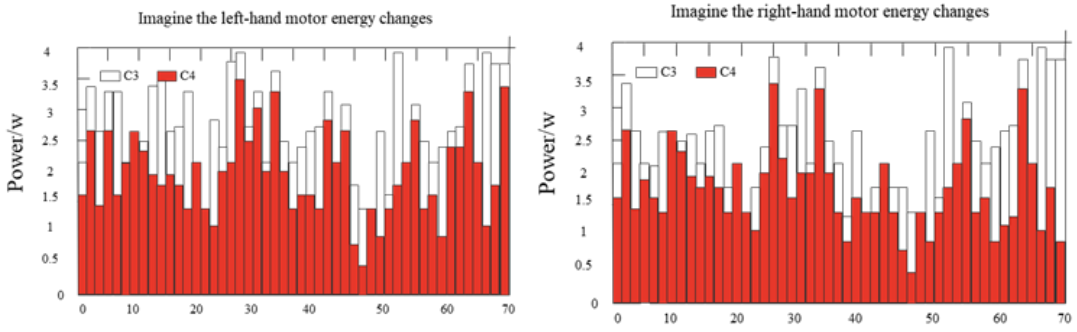



Fig. 8. Feature extraction of AR model.




(a) Imagination the left-hand movement (b) Imagination the right hand movement

Fig. 9. Energy simulation example 4.

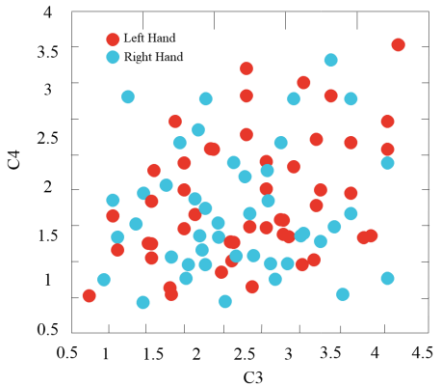
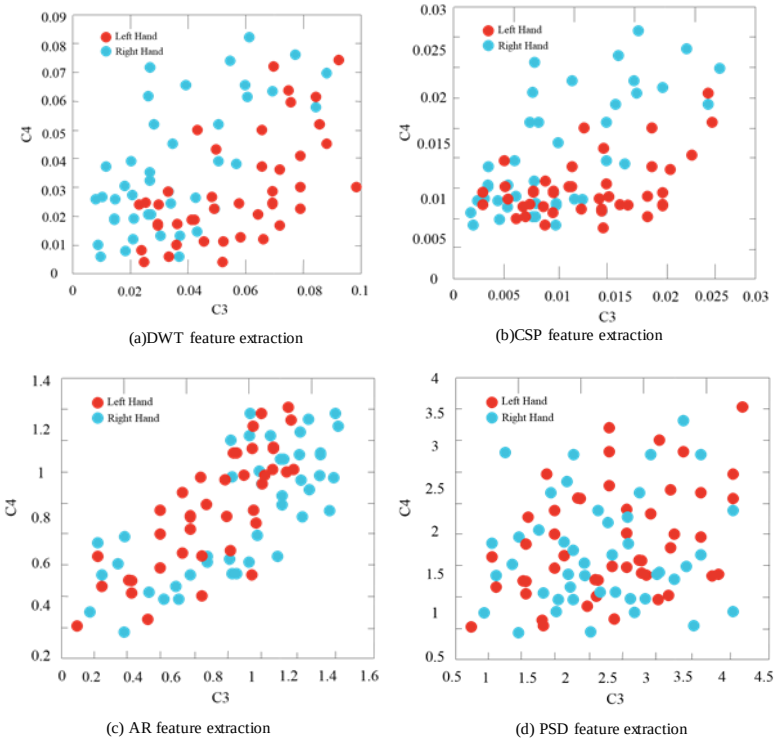



Fig. 10. Feature extraction of PSD.




(a)DWT feature extraction (b)CSP feature extraction

(c) AR feature extraction (d) PSD feature extraction

Fig. 11. Feature extraction quantification scatter plot.

In this paper, taking the EEG signals of C3 and C4 channels as an example, this paper converts the extracted eigenvectors into energy entropy ratios. Its size reflects the complexity of motor imagery, as shown in Fig. 11.

In order to further verify the effectiveness of the method proposed in this paper, experiments are conducted on a wheelchair prototype and some elderly people are invited to use the product. After trying out the product, evaluations are made using a percentage evaluation method, and the experimental results are shown in Table II.

TABLE II. USER EXPERIENCE EVALUATION RESULTS

| No. | User Experience | No. | User Experience | No. | User Experience |
|---|---|---|---|---|---|
| 1 | 90.42 | 9 | 90.17 | 17 | 92.18 |
| 2 | 89.14 | 10 | 90.97 | 18 | 90.03 |
| 3 | 87.08 | 11 | 86.76 | 19 | 87.15 |
| 4 | 90.72 | 12 | 91.71 | 20 | 86.19 |
| 5 | 89.36 | 13 | 88.79 | 21 | 86.30 |
| 6 | 88.13 | 14 | 91.62 | 22 | 92.85 |
| 7 | 86.20 | 15 | 92.97 | 23 | 91.63 |
| 8 | 89.36 | 16 | 86.73 | 24 | 92.78 |

The model is compared and verified with [5] (emotion perception model based on tactile recognition), [6] (intelligent virtual assistant), and [18] (human-computer interaction combined with optical fiber sensor). Its intelligence, humanization, and user experience are evaluated through expert evaluation. A total of five groups of experiments are conducted, and the results are shown in Table III:

### C. Analysis and Discussion

*1) Analysis of experimental results:* Four frequency bands are obtained. The third layer of detail coefficients represents the 8-16Hz frequency band of the original EEG signal, including alpha waves and mu rhythms (Fig. 3).

Fig. 4 illustrates the detailed relationship between imagination and information features, which is also an important foundation of human-computer interaction and the basic setting of theoretical research in this article.

As shown in Fig. 5 and 6, DWT and CSP are combined to extract the features of motor imagery EEG signals, and the feature information of time domain, frequency domain and spatial domain fusion is obtained.

TABLE III. COMPARISON RESULTS OF MODEL PERFORMANCE

| Test parameters | Reference [5] | Reference [6] | Reference [18] | Model in this article |
|---|---|---|---|---|
| Intelligent | 81.80 | 78.92 | 74.52 | 91.26 |
| humanization | 79.22 | 73.01 | 77.08 | 88.84 |
| User Experience | 82.57 | 75.77 | 76.67 | 90.85 |

From Fig. 7 and 8, it can be seen that the model proposed in this paper has good convergence and also verifies the reliability of the model data in this paper.

As shown in Fig. 9, the autocorrelation function $\hat{R}x(m)$ at point $(2m-1)$ of a piece of EEG signal sequence x(n) collected, with length N, is calculated.

From Fig. 10, it can be seen that the model proposed in this paper performs well in data feature extraction and has a significant clustering effect.

As shown in Fig. 11, the frequency bands containing the ERS/ERD phenomenon extracted by DWT are extracted by CSP, and the feature information includes not only time-frequency domain information, but also spatial information, which is suitable for two types of motor imagery tasks.

Through the above research, it is verified that the interactive design method of products for the elderly based on human interaction proposed in this paper has a good effect, and can effectively improve the design effect of products for the elderly.

As can be seen from Table II, the user experience evaluations of the model products proposed in this paper are all above 86 points, and the highest score reaches 93 points. Therefore, the product proposed in this article has received good feedback from the user group, which also verifies the effectiveness of the model and the practical effect of the model method proposed in this article.

In Table III, the model proposed in this paper is superior to the existing models in terms of intelligence, humanization and user experience, and the user experience is far superior to the existing models. This shows that the model not only has good performance, but also has significant application advantages.

*2) Product design needs for the elderly:* The product design must determine the user's use needs according to the demand analysis, define the product's functions and characteristics based on the needs, and create a conceptual design scheme. After that, the scheme needs to be evaluated by human-computer interaction experts or actual users, and effective feedback should be put forward to facilitate design improvement. The concept of interaction design is involved here, and interaction design is a design field that defines or designs the behavior of artificial systems. It defines the content and structure of communication between multiple interactive individuals, so that interactive individuals can cooperate with each other and achieve certain goals.

For example, the smart home service terminal is designed to provide people with a healthy, safe, comfortable, environment-friendly and convenient living environment. Its design concept basically follows the concept of ease of use, reliability, standardization and humanization, which can create a comfortable living environment for the elderly in their later years. In the application of interpersonal interaction, smart home service terminals must be easy to use and convenient for the elderly. In fact, many elderly people's understanding of scientific and technological products, such as smart phones, is still in the era of button phones. The elderly often have no idea how to use smart phones, so the market is full of large screen button phones suitable for the elderly. The purpose is to facilitate their use, and smart home service terminals also need to meet the needs of facilitating the use of the elderly. In order to ensure the safety of the elderly when using these service terminals, it is necessary to ensure the reliability of terminal operation. Therefore, if there is a problem with the product, it must be able to solve it as quickly and efficiently as possible. In addition, the designed products must conform to the national or industrial standards. If there is no standard, quality cannot be guaranteed. Furthermore, according to the above analysis, the cognitive and receptive abilities of the elderly will deteriorate as they age. Smart home service terminals should improve the humanized experience in a simple and easy-to-use way, so that the elderly can easily use modern digital household appliances. Therefore, the following functions are designed on the smart home service terminal.

It includes intelligent reminder function. For example, when the elderly are alone at home, they may fall asleep while watching TV on the sofa. When a certain time is reached, relevant sensors (such as pressure sensors) installed on the sofa and intelligent video terminals at home will feed back information to the terminal system, and the system will send out reminders (including voice reminders and slight vibration reminders). If the elderly do not follow up after the reminder, they need to determine whether to notify their family members (this function is an advanced application and is currently difficult to implement). The automatic control of smart home appliance control functions, such as air conditioning, lighting, air purifiers, humidifiers, etc., is achieved by using temperature and humidity sensors. When the indoor temperature and humidity reach the set value, the service terminal automatically controls relevant equipment to adjust the indoor environment. For the automatic detection and alarm function, such as using surveillance cameras and some wearable medical devices, when the elderly encounter some abnormal situations indoors, the terminal system will automatically connect to the Internet to alarm and notify the guardian. In addition, it uses motion recognition, voice recognition and other technologies to achieve more convenient interpersonal interaction control, which is convenient for the elderly to use. For example, when the elderly want to watch TV, they cannot operate the smart flat-screen TV. At this time, they can choose to use the human-computer interaction intelligent control function of the service terminal to control the operation of home appliances by voice. The service terminal should remind the elderly how to operate modern household appliances in the form of voice, and give clear steps and precautions. The service terminal connects to the home broadband network, automatically downloads the driver or patch on a regular basis, and automatically installs the maintenance system. When the system has problems, it automatically sends information to notify the maintenance personnel for remote maintenance or on-site maintenance.

*3) Limitations of the study and follow-up work:* The demand for elderly products is very high, especially with the increasingly severe aging population. People have a higher demand for intelligent elderly products, and the high cost and

requirements of elderly products also pose certain challenges to the design of elderly products.

The amplitude of EEG signals is very low, only at the millivolt level, and is susceptible to interference. Pre-processing is necessary before analyzing EEG signals, which can affect the effectiveness of feature extraction. Select scientific and objective preprocessing methods to minimize interference in the signal to the greatest extent possible. This article simulates the extraction of EEG signals through simulation, but there may be some systematic errors in reality. Therefore, further improving the accuracy in the future is the key to applying the model in practice.

Based on the current popularity of intelligent products and 4G/5G networks, the communication needs of elderly products have been guaranteed. Therefore, improving the anti-interference ability of the model in this article can further enhance the intelligence of the designed product. Moreover, the method in this article does not require high production costs and has certain universality.

In addition, this paper needs to further integrate psychological factors, consider the actual needs of the elderly, and combine the needs of the elderly with psychology to further improve the practical effectiveness of the model in this article.

## V. Conclusion

Aging is the trend of world population development and a symbol of the continuous advancement of human civilization. At the same time, social and cultural trends such as digitalization, multiculturalism, experience economy, and postmodernism are sweeping in. Its core is dematerialization, emotionalization, individuation and diversification. The projection of these cultural trends has profoundly affected the life, entertainment, social interaction and other aspects of the elderly group. As the development carrier of human civilization, aged products are showing the characteristics of the times such as “exclusion”, “contradiction” and “integration”. This paper combines the idea of human-computer interaction to analyze the product design system for the elderly, so as to improve the user experience and service effect of the product for the elderly. Moreover, the experimental study verifies that the interactive design method of products for the elderly based on human interaction proposed in this paper has a good effect, and can effectively improve the design effect of products for the elderly.

Due to the current theoretical research stage of brain computer interfaces, many scientific and technological problems have not yet been solved. The paper proposes that the research on intelligent interactive terminal control based on EEG is an important topic. Although certain achievements have been made in the simulation verification of algorithms such as EEG signal preprocessing, feature extraction, and classification recognition, there are also some problems that need further improvement: the amplitude of EEG signals is very low, only at the millivolt level, which is susceptible to interference. Pre-processing is necessary before analyzing EEG signals, and the results will affect the effectiveness of feature extraction. At the same time, it is necessary to select scientific and objective preprocessing methods to minimize interference with the signal. Secondly, data processing is in an offline state, so it is necessary to study online brain computer interface systems to verify the effectiveness of the theoretical methods proposed in the paper.

Based on the above analysis, the main research needed in the future is to improve the system error of the model proposed in this paper and construct an online model to further enhance the online intelligent interactive simulation effect of the model.

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# Analyzing RGB and HSV Color Spaces for Non-Invasive Blood Glucose Level Estimation Using Fingertip Imaging

Asawari Kedar Chinchanikar[1], Manisha P. Dale[2]
Department of Electronics and Telecommunication, AISSMS Institute of Information Technology, Pune, India[1]
Department of Electronics and Telecommunication, MES Wadia College of Engineering, Pune[2]

***Abstract*—Traditional blood glucose measurement methods, including finger-prick tests and intravenous sampling, are invasive and can cause discomfort, leading to reduced adherence and stress. Non-invasive BGL estimation addresses these issues effectively. The proposed study focuses on estimating blood glucose levels (BGL) using "Red-Green-Blue (RGB)" and "Hue-Saturation-Value (HSV) color spaces" by analyzing fingertip videos captured with a smartphone camera. The goal is to enhance BGL prediction accuracy through accessible, portable devices, using a novel fingertip video database from 234 subjects. Videos recorded in the "RGB color space" using a smartphone camera were converted into the "HSV color space". The "R channel" from "RGB" and the "Hue channel" from "HSV" were used to generate photoplethysmography (PPG) waves, and additional features like age, gender, and BMI were included to improve predictive accuracy. To enhance the precision of blood glucose estimation, the Genetic Algorithm (GA) was used to identify the most significant and optimal features from the large set of features. The "XGBoost", "CatBoost", "Random Forest Regression (RFR)", and "Gradient Boosting Regression (GBR)" algorithms were applied for blood glucose level (BGL) prediction. Among them, "XGBoost" yielded the best results, with an $R^2$ value of 0.89 in the "RGB color space" and 0.84 in the "HSV color space", showcasing its superior predictive ability. The experimental outcomes were assessed using "Clarke error grid analysis" and a "Bland-Altman plot". The Bland-Altman analysis showed that only 7.04% of the BGL values fell outside the limits of agreement (±1.96 SD), demonstrating strong agreement with reference values.**

***Keywords*—Blood glucose; Photoplethysmography; non-invasive; Genetic Algorithm; XGBoost; RGB; HSV**

## I. INTRODUCTION

"Diabetes" is a severe, endless illness in which the body is unable to produce enough insulin or cannot effectively use the insulin it produces. As per the report of the "International Diabetes Federation (Diabetes Atlas 2021)" [1], the number of individuals with diabetes in "Southeast Asia" is expected to increase by 68%, reaching 152 million by 2045. In 2021, diabetes was the cause of 747,000 fatalities. Over 50% of adults with diabetes remain undiagnosed. This is because current methods are invasive. Invasive methods include laboratory techniques or using glucometers at home. These methods cause discomfort due to the need for pricking, and they only provide a snapshot of glucose levels at that moment. It is very inconvenient for patients having "type-1 or type-2 diabetes" to collect blood samples multiple times a day as they need to adjust their insulin doses and make necessary changes to their diet or physical activities. The discomfort from frequent finger pricks may discourage some patients from regularly monitoring their glucose levels. Hence patients seek more convenient and non-invasive options for continuous glucose monitoring.

"Non-invasive blood glucose estimation" is painless, comfortable, user friendly, economical, minimizes infection risks, offers continuous monitoring, promotes better adherence, and is appropriate for individuals of all ages. Research is ongoing into various "non-invasive blood glucose estimation" methods, including the use of "saliva" [2], "sweat" [3], "photoacoustic spectroscopy" [4], "Mid-infrared (MIR) spectroscopy" [5], "Near-infrared spectroscopy (NIR)" [6-10]. PPG-based near-infrared spectroscopy is highly admired for its ability to provide non-invasive, real-time monitoring of vital physiological parameters, combining the benefits of PPG's surface-level monitoring and NIR's deeper tissue analysis. In this technique, an optocoupler pair that consists of a "light source and detector" in the wavelength range of 700 nm to 2500nm is directed onto the target. This light interacts with the blood components, undergoing scattering, absorption, and reflection. The amount of light received after interaction changes in direct proportion to the BGL in the blood, according to the Beer-Lambert law [11]. By measuring these intensity changes, the receiver can detect and quantify the presence of glucose molecules within the blood vessels.

A smartphone is a versatile and powerful device that can perform various tasks beyond its primary role of communication. As per Statista's report [12], the smartphone user base in India was expected to exceed one billion in 2023 and is estimated to reach 1.55 billion by 2040. Smart phone technology [13] has been advancing rapidly in the healthcare industry, driven by high-resolution cameras, built-in sensors, innovative applications, and enhanced network connectivity with healthcare providers. Due to technological advancements, smartphone cameras can now function as sensors and can be used to estimate heart rate[14], hemoglobin [15-20], blood glucose [16-17], [21-22], and breast cancer [23].

There is an option to use different color spaces to estimate various physiological parameters from a video recorded with a smartphone. Researchers have reported varying performance levels depending on the selection of color pixels from videos. In [15-17], the "RGB color space" was utilized to estimate hemoglobin and blood glucose levels. Hasan et al. [18]

transformed "RGB" video data into different color spaces, such as "hue (H), saturation (S), value (V), lightness (L), a, b (a and b for the color dimensions) and gray (g)" to estimate hemoglobin. Hasan et al. [19], observed that the "RGB" pixel intensities of video frames were transformed into the "HSV color space" for hemoglobin level estimation. Fan et al. [20], utilized the "a parameter" of the "L*a* b color space" to predict hemoglobin concentration. The Red channel in "RGB color space" is more susceptible to lighting variations, leading to noise in the signal. In contrast, the "Hue channel" in "HSV color space" is more resilient to lighting fluctuations, making it a better choice in uncontrolled or variable lighting conditions.

In previous studies, BGL estimation from fingertip videos has predominantly relied on features extracted from the "RGB color space". However, the "RGB color space" may not always fully capture the range of information relevant to blood glucose levels, as it is sensitive to variations in lighting and may not effectively represent subtle color changes associated with physiological fluctuations. To address this limitation, the proposed study opted to explore both "RGB" and "HSV color spaces" independently. The "HSV color space" offers distinct advantages over "RGB color space", as it separates color information into three components: "hue, saturation, and value". This separation enhances its ability to handle lighting variations and makes it more sensitive to color changes that are linked to physiological changes such as BGL fluctuations. By analyzing and modeling the data separately in both "RGB" and "HSV color spaces", the proposed study aimed to compare the effectiveness of each color space in capturing relevant features for accurate BGL estimation. This dual approach allows for a more comprehensive understanding of how each color space contributes to BGL estimation and provides valuable insights into which may be more effective for non-invasive glucose monitoring. The comparative evaluation of "RGB" and "HSV" can help identify optimal feature extraction methods, ultimately improving the robustness and reliability of predictive models for blood glucose estimation.

Proposed study recorded fingertip videos using a smartphone camera and an external light source. The recorded videos were processed in "RGB" and "HSV color spaces", with the "RGB" pixels being converted into the "Hue, Saturation, and Value (HSV)" representation. PPG signals were extracted from the captured video in both color spaces. Machine learning models were developed to forecast BGL based on features derived from the "PPG signal". The performance of both color spaces was analyzed. The main aspects of proposed work are included:

*1)* One significant contribution of this work is the creation of a new fingertip video database, which features recordings from 234 subjects.

*2)* A custom stabilization box was designed and developed to securely hold the Near-Infrared (NIR) LED module, the finger, and the smartphone camera, ensuring stability during fingertip video recording.

*3)* A Streamlit-based application was developed to assess the quality of recorded fingertip videos for PPG signal extraction. This tool facilitated the efficient evaluation of video recordings, ensuring they met the required quality standards for successful signal extraction.

*4)* As part of the contribution, "RGB" and "HSV color spaces" were utilized to estimate BGL, with "RGB" pixel values converted into the "HSV color space". The model's performance was evaluated in both color spaces to assess the impact of color representation on model accuracy.

The paper is organized as follows: Section II provides a review of the literature, highlighting key studies and methodologies relevant to the field. Section III offers an overview of the proposed system and methodology. Section IV focuses on the processing of PPG signals in detail, while Section V delves into the details of the feature extraction process. Section VI covers feature selection and model construction, emphasizing the methods employed to create an accurate prediction model. Section VII showcases the study's findings, and finally, Section VIII wraps up the paper, emphasizing the key findings and contributions of the work.

## II. Related Work

Recent work has emphasized various "non-invasive techniques" for monitoring BGL. Researchers have utilized sensors to estimate BGL by analyzing interstitial fluid. Specific sensors were designed to measure BGL based on optical and non-optical techniques.

Rodin et al. [3], developed a biosensor for measuring blood glucose through sweat analysis. The results were stored on a smartphone linked via "Bluetooth". They calculated the "Mean Absolute Percentage Error (MAPE)" by comparing the obtained values with those from a glucometer using a t-test. Accuracy was assessed through correlation analysis, and "linear regression (LR)" was applied, revealing a maximum error range of 7.40 to 7.54%. The study involved 200 subjects.

Wei et al. [24] assessed BGL using the Skin Oxygen Saturation Imaging System (SOSI) to estimate glucose levels based on light absorption differences. The setup included a Flea 2 CCD camera, an infrared thermal camera, and calibration tools for accuracy. Five subjects aged 22 to 46 participated, with glucose levels monitored before and after meals. Oxygen saturation data was analyzed to estimate glucose concentrations, showing a postprandial glucose increase with variations from 0.38 to 0.92 mmol/L. However, the limited sample size of only five subjects is a drawback, requiring further studies with larger populations to validate the findings and improve reliability.

PPG acquired by pulse oximeter, which works in the NIR region, is an affordable, "non-invasive optical technique" that detects variations in the blood flow within arteries. Monte- Moreno [6], employed a PPG sensor to record the PPG signal and an "activity detection module" to filter out artifacts and avoid signal loss due to finger movement. Additionally, a "signal processing module" was used to derive the primary features. PPG data was recorded for 410 individuals. The predictive models included "Ridge linear regression", a "Multilayer perceptron neural network", "Support Vector Regression (SVR)", and "RFR". Out of these models, the "RFR" delivered the best result with an "R2 value" of 0.90.

Habbu et al. [7], proposed a data acquisition system based on optical sensors operating at 920 nm to record PPG signals. The PPG data was collected for 611 subjects, with each session lasting 3 minutes. They extracted 28 features through single pulse analysis and trained a neural network, achieving an R2 value of 0.91.

Jain et al. [8], developed a system utilizing "NIR spectroscopy" and "machine learning". The device is integrated within an "Internet of Medical Things (IoMT) framework", allowing patients and doctors to access it via the cloud. A noninvasive glucometer has been introduced, utilizing "short NIR waves" with "absorption" and "reflectance of light" at "specific wavelengths, 940 nm and 1,300 nm". A "Deep Neural Network model (DNN)" was employed, and the accuracy was evaluated using Clarke Error Grid analysis, achieving 100% accuracy. The study involved 97 participants.

Joshi et al. [9], proposed using NIR spectroscopy within an IoMT framework for glucose monitoring. A "dual NIR spectroscopy" technique has been proposed, incorporating "absorption and reflection spectroscopy" at 940 nm and absorption spectroscopy at 1,300 nm. "DNN" was implemented for sensor calibration, while "polynomial regression models" were utilized to predict serum glucose levels. 200 subjects were included and reported an accuracy of 100%.

Recently, many smartphones have incorporated sensor systems that enable real-time heart rate and oxygen saturation measurement through PPG. These non-invasive techniques are becoming increasingly popular due to their distinct benefits, such as ease of use, painlessness, no risk of infection, and the ability to deliver instant results. Golap et al. [16], proposed imaging plethysmography (IPPG) for estimating blood glucose and hemoglobin levels. Fingertip videos were recorded with a smartphone camera, using a NIR LED board for light illumination. The NIR board comprised 850 nm NIR LEDs and one flash LED. A 15-second video was captured from 111 subjects. "RED channel" was employed to extract the "PPG signal". A 500 × 500-pixel section was selected from the right- to-left part of the frame as a "Region of Interest (ROI)". Forty-six "time and frequency domain" features, along with age and gender, totalling 48 features, were used to train the predictive model. Correlation-based feature selection through "Multigene Genetic Programming" (MGGP) was recommended. "SVR", "LR", "RFR", and "MGGP symbolic regression" were employed. The MGGP-based model achieved an R2 value of 0.88 on the test dataset.

Haque et al. [17], developed a "DNN" model to access hemoglobin, glucose, and creatinine levels using "PPG signals". A NIR LED board (850 nm) and a "smartphone camera" was used to record fingertip videos, and the "PPG signal" was extracted from the "RED channel". A 500 × 500-pixel section from the right-to-left portion of the image was chosen as the ROI. The study included 93 subjects, and 48 "time and frequency domain features", including age and gender, were derived. "Correlation-based feature selection (CFS)" with "Genetic Algorithms (GA)" was employed and achieved an R2 value of 0.902 for estimating BGL.

Islam et al. [22] used a front-facing camera to capture fingertip videos from 52 subjects, recording between 20 to 50 seconds. The "RED channel" was selected to derive the "PPG signal". Various predictive models to estimate glucose levels, including "Principal Component Regression (PCR)","Partial Least Squares Regression (PLS)", "SVR", and "RFR". Among these models, the "PLS model showed the optimum "standard error of prediction (SEP)" at 17.02 mg/dL.

Limited research has been conducted on non-contact BGL estimation. Nie et al. [25], developed the technique for BGL prediction based on IPPG combined with machine learning. The near-infrared industrial camera operating at 940 nm was used to capture video from the face, focusing on the cheek area as the region of interest. The study involved eight adults who recorded 1-minute videos. A total of 1280 videos were collected along with an oral glucose tolerance test (OGTT). Weighted averaging of pixel values were used to extract the PPG signal, from which 26 features were derived, including time-domain, energy- domain, and human physiological parameters. Correlation-based feature selection was employed and tested various machine-learning models, including "PCR, SVR, RFR, and PLS". The best results were achieved with RFR, reporting a "Mean Absolute Error (MAE)" of 1.72 mmol.

Different approaches have been investigated to process "PPG signals", extract prominent features, and optimize these features for improved performance. Chen et al. [26], presented a novel algorithm to detect "beat onsets and peaks" from noisy "PPG waveforms". Subohet al. [27], explored the use of derivative waveforms and inflection points for accurate detection of PPG, VPG, and APG peaks, enhancing diagnostic precision. McDuff et al. [28], introduced an automated approach for identifying "systolic and diastolic peaks" in a "PPG waveform" recorded remotely with a digital camera. Takazawa et al. [29], highlighted that the "second derivative of the PPG (SDPTG) waveform" serves as a valuable indicator of vascular health. Specifically, the b-c-d-e/a ratio has been widely used to assess vascular aging and the influence of vasoactive agents, making it particularly relevant in the evaluation of cardiovascular conditions. Rubins et al. [30] demonstrated that PPG-derived parameters, including "Digital Volume Pulse (DVP), augmentation index (AIx), and reflection index (RI)", exhibit significant variations between healthy individuals and cardiovascular patients. Esper et al. [31], highlighted that arterial waveform analysis, beyond blood pressure monitoring, provides key hemodynamic parameters like "stroke volume (SV), cardiac output (CO), vascular resistance, SV variation (SVV), and pulse pressure variation (PPV)" in clinical settings. Seitsonen et al. [32], highlighted the importance of multimodal monitoring in assessing analgesic adequacy, demonstrating that a logistic regression model incorporating "EEG response entropy, ECG RR-interval, and PPG notch amplitude" achieved the highest classification accuracy. Baek et al. [33], introduced the "second derivative of photoplethysmography (SDPTG)" as an advanced application of PPG for assessing arterial stiffness and aging. The SDPTG waveform comprises five distinct waves as a, b, c, and d in the "systolic phase" and e in the "diastolic phase" with its pattern defined by the ratios of the b, c, d, and e waves to the primary a wave. Xiao et al. [34], demonstrated that the "Stress- Induced Vascular Response Index (sVRI)", derived from "PPG", effectively assesses cognitive load during gaming, enabling real-time evaluation of players" mental workload and

informing game design optimizations. “Genetic Programming” (GP), introduced by Koza [35], is an evolutionary algorithm that evolves computer programs to solve problems like Boolean function learning and symbolic regression using principles of “survival of the fittest” and “genetic crossover”. Thanathamathee et al. [36], employed an enhanced XGBoost framework integrating SHAP-based instance weighting and Anchor Explainable AI to address class imbalance and improve interpretability in financial fraud detection.

In existing literature, various sensor-based methods have been employed to estimate blood BGL, demonstrating the potential of non-invasive monitoring. These sensors often require physical contact or attachment to the body, which can limit user comfort and accessibility. In contrast, smartphone cameras have emerged as a promising alternative for BGL estimation, with several studies leveraging the RGB color space to analyze fingertip videos. This approach benefits from the widespread availability of smartphones, offering a practical and affordable option for continuous monitoring.

Previous smartphone-based methods to estimate BGL were limited by small sample sizes, which hindered the ability to draw broad conclusions and generalize findings across diverse populations. Smaller sample sizes failed to adequately represent variations in key demographic factors, such as age, gender, and different glycemic conditions, thereby reducing the robustness and applicability of the results. Furthermore, many studies did not include individuals with varying medical conditions like hypertension or diverse glycemic conditions (e.g., hyperglycemia and hypoglycemia), which were crucial for understanding how these factors could influence blood glucose estimation. In contrast, the proposed study addressed these gaps by using a comparatively larger sample size, which enhanced the robustness and reliability of the findings. The variability in the sample, encompassing a broader range of age groups, gender distributions, and glycemic conditions, ensured a more comprehensive understanding of blood glucose estimation across different population subgroups. This diversity allowed for improved generalization of the results, making the study more applicable to real-world settings where individual health conditions and demographic factors varied widely. By including subjects with conditions such as hypertension and varying glycemic states, the proposed study provided a more accurate representation of the broader population, helping to overcome the limitations of prior research.

Previous research on fingertip video capture using smartphones and NIR-LED boards showed that slight finger movements or camera shakes during data collection could introduce motion artifacts, distorting PPG signals and compromising the accuracy of BGL estimations. Despite efforts to instruct participants to keep their fingers still, these studies overlooked natural movements like finger shifts, hand tremors, and slight camera shifts caused by breathing, all of which could notably affect the quality of the PPG signals. Even subtle variations in video frames could lead to erroneous feature extraction and unreliable blood component level predictions. To address these limitations, the proposed work introduced a custom stabilization box designed to minimize motion artifacts and ensure more stable and consistent video capture. This new approach aimed to improve the reliability of the PPG signal acquisition process by mitigating the effects of unintentional movements during data collection, providing a more robust and accurate estimation of blood components.

Building upon this work, the proposed study explored the effectiveness of the “HSV color space” in estimating BGL alongside the widely used “RGB color space”. Specifically, fingertip videos captured via a smartphone camera were analyzed to evaluate the effectiveness of both color spaces. While the HSV color space is often considered more robust for color-based applications due to its separation of chromatic content. In the reviewed literature, one notable limitation when recording video using a smartphone for BGL estimation was the lack of a built-in mechanism to assess video quality. Even slight movements, whether of the smartphone or the subject, could lead to video distortions or blurriness, significantly affecting the reliability of the data. This resulted in the collection of suboptimal or unusable video data, potentially rendering the entire database ineffective for accurate analysis. To address this issue, a Streamlit-based application was developed in the proposed work. This application enabled immediate quality checks, ensuring that only top-quality, reliable video data was included in the database, thus improving the accuracy and effectiveness of the BGL estimation process.

## III. METHODOLOGY

The proposed system model, as illustrated in the Fig. 1, depicts the overall operational flow and operational flow of the setup. It begins with data collection, where relevant information was gathered using smartphone camera. The collected data was then passed through signal extraction and processing steps to remove noise and ensure the data was in a usable format. Following this, feature selection was performed to identify and extract the most significant features that contributed to accurate predictions or classifications. The selected features were subsequently used for model building, where machine learning techniques were applied to develop a predictive or analytical model. This comprehensive flow ensured that the system effectively processed raw data, optimized the input features, and generated accurate, actionable outcomes.

### *A. Experimental Setup*

The hardware setup for the BGL estimating system included a NIR LED module and a smartphone camera. The NIR LED module comprised six surrounding NIR LEDs and one flash LED. The flash LED was employed to enhance the light intensity of the NIR LEDs. The proposed study utilized a 940 nm NIR LED board because blood glucose demonstrates significant absorption properties in the NIR range, with an absorption peak between 940 nm and 1000 nm, as illustrated in Fig. 2.

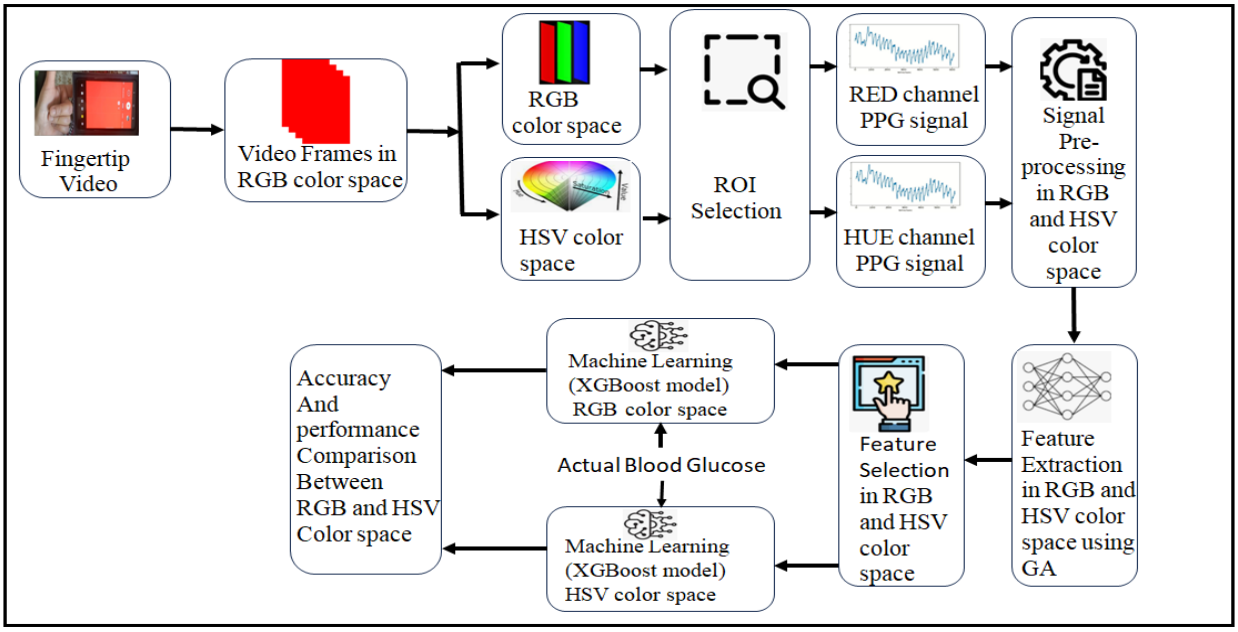



Fig. 1. Proposed model design.

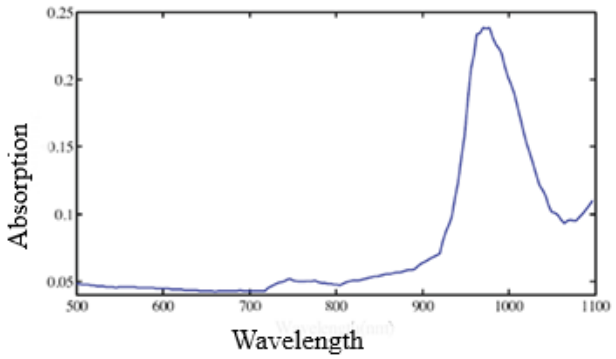
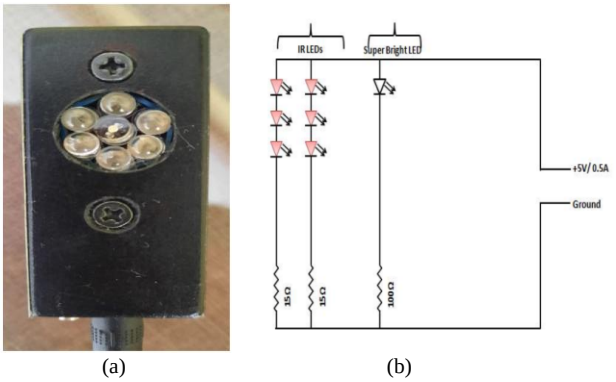



Fig. 2. Absorption spectrum of blood glucose in the NIR light range.

Fig. 3(a) illustrates the NIR LED module, which includes six outer NIR LEDs and a central flash LED, and Fig. 3(b) shows its design. NIR LEDs were employed to illuminate the finger.




(a) (b)

Fig. 3. (a) NIR LED module, (b) Module design.

## B. Data Collection

In proposed study, fingertip videos in *.mp4 format were recorded from 234 subjects, consisting of 122 females and 112 males. The subject's ages ranged from 22 to 88 years, with their weights ranging from 45 to 120 kg. The dataset includes "diabetic" subjects ("Type 1 and Type 2") and "non-diabetic" subjects, with BGL ranging from 90 to 480 mg/dL (milligrams per decilitre). The subjects included in the proposed work were diverse in terms of socio-economic background, physiological condition, dietary habits, workout routines, and weight variations, ensuring a thorough representation of the population. This diversity strengthens the generalizability and robustness of the results. Data collection occurred at various local societal institutions in Pune. A "15-second video" of the "right-hand index fingertip" was recorded for each subject.

The subjects willing to participate in this research were provided with a brief overview of the problem statement. Following this, a consent form was signed by each subject. Additionally, a detailed record of each subject's history was maintained, including information on daily dietary habits, workout routines, and any surgical background. All personal information and identities of the subjects were kept confidential to ensure anonymity and protect their privacy.

The subjects were first instructed to clean their hands with soap and dry them thoroughly. They were then asked to settle down for 5 minutes to ensure a relaxed state before the video recording. Prior to recording the fingertip videos, the subjects applied hand sanitizer to maintain proper hygiene. They were also advised to avoid wearing nail polish to ensure accurate video capture of the fingertip. Once the video recording was completed, BGL was measured using an Accu-Check blood glucometer, which features an enzyme system based on Flavin-dependent glucose dehydrogenase (FAD-GDH) and operates through electrochemical sensing for precise glucose measurement. The subjects were directed to position the tip of their "right index finger" on the "NIR LED module", while the smartphone camera was positioned on the opposite side to record the video. The videos were recorded using a Samsung A51 smartphone, which operates on Android 10 and is equipped

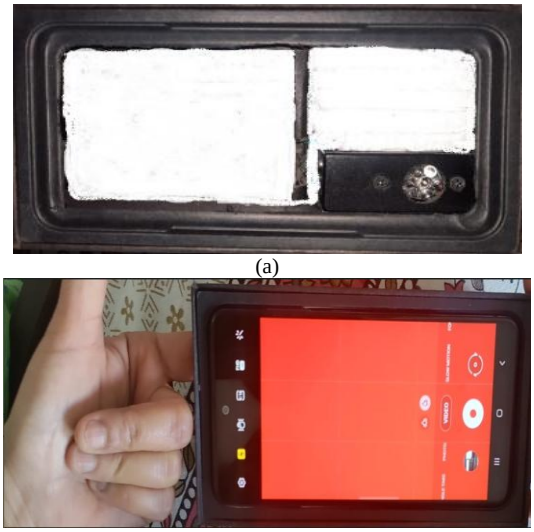
with a 48 MP camera, capturing 30 frames per second at a display size of 1080 x 2400 display dimensions.

Several issues were encountered during data collection with the experimental setup.

- The NIR LED board could shift when the finger was placed on it.
- The finger might also move on the NIR LED board due to discomfort.
- Slight movement of the smartphone camera occurred during video capture, often caused by breathing.

To address these issues, several remedial actions were implemented. The NIR LED board was securely fixed inside an empty box to prevent shifting. A slot was created in the box wall, allowing the finger to be easily placed on the NIR LED board while minimizing movement. Furthermore, a slot was added at the upper section of the box to properly position the smartphone properly, ensuring the camera could record videos without movement. The designed box is demonstrated in Fig. 4.

Despite designing a box to minimize movement while recording the video, extracting a clean PPG signal remained challenging due to interruptions such as sneezing, coughing, or small finger movements caused by breathing. To address this, a Streamlit application was developed. "Streamlit" is an "open-source Python library" that enables the creation of "interactive web applications" for "data science and machine learning projects", allowing users to create web-based interfaces for Python scripts without needing front-end development expertise. The video quality for the extracted PPG signal was evaluated using this Streamlit application. After recording the video with acceptable quality, the blood glucose level was measured using an Accu-Check® instant blood glucose meter. The window of the Streamlit application is displayed in Fig. 5.



(a) (b)

Fig. 4. (a) Designed box, (b) The finger and smartphone positioned in the designated slots.


Fig. 5. Streamlit application window.

## IV. PPG Signal Generation

PPG wave is extracted from recorded fingertip video. The initial "3 seconds" and the final "2 seconds" of the video were removed to remove distorted frames. As a result, 300 frames were extracted from the video for each subject. The recorded videos ware in the "RGB color space". The "PPG signal" was derived from the original videos in the "RGB color space" and the converted "HSV color space" by transforming the "RGB" pixels into "HSV". The conversion of "RGB" to "HSV" consists of normalizing the BGR values to the range [0, 1]; each color component is divided by 255, producing the normalized values $B'$, $G'$, and $R'$. To determine the maximum ($C_{max}$) and minimum ($C_{min}$) values, find the highest and lowest values among the normalized blue, green, and red components. Next, calculate the variation ($\Delta$) between the highest and lowest values. Afterward, the hue (H) is determined by using the following Eq. (1) and (2).

$$H = 60 \times \frac{G' - B'}{\Delta} \quad (\text{if } G' > B') \tag{1}$$

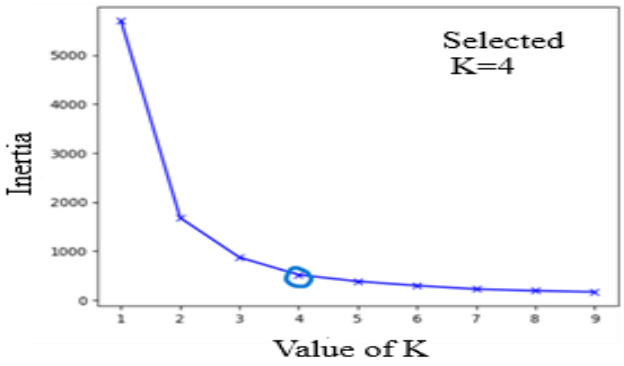
$$H = 60 \times \frac{G' - B'}{\Delta} + 360 \ (\text{if } G' < B') \tag{2}$$

The process for extracting the PPG signal was identical in both color spaces. Choosing the appropriate channel was crucial for extracting the "PPG signal" from a recorded video. The average pixel brightness values for the "Red, Green, and Blue channels" were calculated in the "RGB color space". It was found that the "Red channel" had the greatest pixel intensity, exceeding 200, while the "Green" and "Blue channels" had pixel

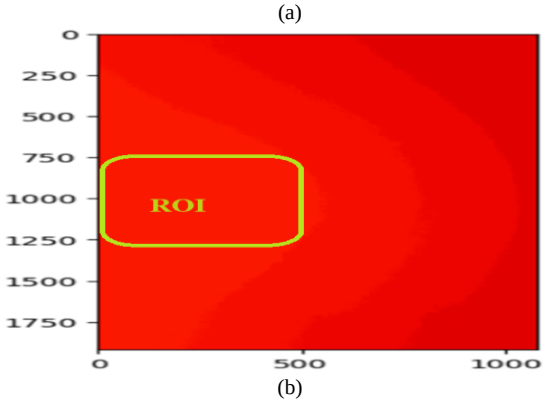
values ranging from 60 to 70. Consequently, it was observed that when the pixel intensity in an image was below 200, extracting the key features from the "PPG signal" became challenging. As a result, the "Red channel" was chosen for PPG signal extraction. In the "HSV color space", the Hue channel was used to extract the PPG signal because it directly represents the color type (e.g. red, blue, green) based on its position on the color wheel. Unlike Saturation and Value, which can vary with lighting conditions, Hue is less affected by changes in lighting or brightness. This stability made the "Hue channel" more reliable for PPG signal extraction.

To define the ROI, "K-means clustering" was applied to video frames to segment pixel intensity values into distinct clusters, enabling the identification of the ROI. "K-means clustering" is an "unsupervised machine learning algorithm". The algorithm begins by randomly selecting "K centroids" and then allocates each pixel to the closest centroid in successive steps, recalculating the centroids as the average of the pixel values within each cluster. This process proceeds until the centroids remain unchanged, indicating convergence. In "K-means clustering," inertia was calculated as the total of "squared distances" between each data point and its corresponding "cluster centroid", which indicates how closely the points are grouped within each cluster. The Eq. (3) for inertia is provided, and the elbow graph used to determine the value of K is shown in Fig. 6(a). Fig. 6(b) displays four clusters with distinct pixel intensity values.

$$\text{Inertia} = \sum_{i=1}^{k} (\text{Nearest Centroid distance})^2 \qquad (3)$$




(a)




(b)

Fig. 6. (a) Elbow graph, (b) Image frame showing ROI.

Based on the above, a 500x500 pixel region from rows 750 to 1250 and columns 0 to 500 was used as ROI to calculate the average intensity for Red and Hue channels. Thus, the raw PPG signal was obtained by taking mean of the pixel values Eq. (4) of the "red channel" and "Hue channel" within the ROI.

$$PPG(t) = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} PPG(i,j,t) \qquad (4)$$

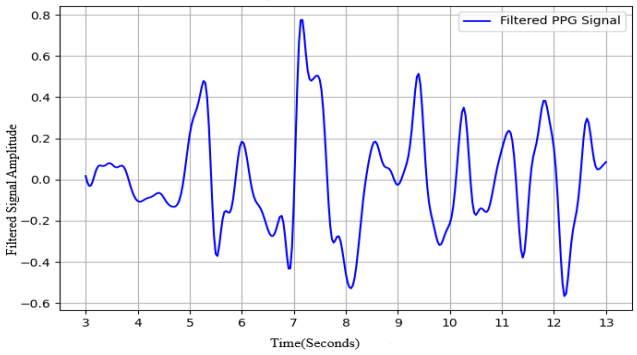
where, M and N represent the dimensions of the ROI, and PPG(i,j,t) denotes the pixel value at position (i, j) at time t.

Applying suitable preprocessing methods was essential for the precise analysis of the PPG signal. A 10-second video from each subject, consisting of 300 frames, was used. The Butterworth band-pass filter is ideal for pre-processing PPG signals because of its flat passband, sharp roll-off, and consistent performance. Therefore, a "Butterworth BPF filter" with a "low cutoff frequency" of 0.5 Hz and a "high cutoff frequency" of 4 Hz was used to clean the extracted PPG signal in both color spaces, designed to support a heart rate range of 30 to 240 beats per minute. The filtered "PPG signal" is demonstrated in Fig. 7(a).

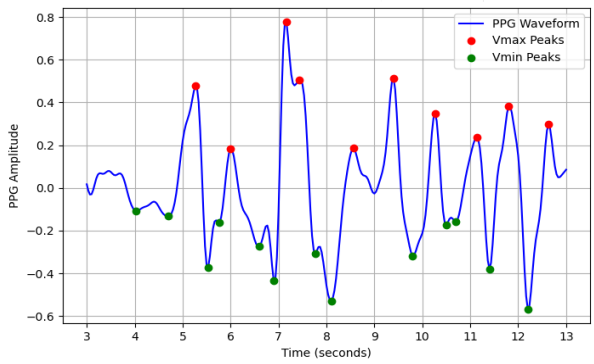
After filtering the raw "PPG signal", a "peak detection algorithm" was employed to locate the peaks in the signal. Before applying the "peak detection algorithm" to the filtered signal, a moving average filter was applied to reduce noisy fluctuations.

$$y[i] = \frac{1}{K} \sum_{j=1}^{K-1} X[i+j] \qquad (5)$$

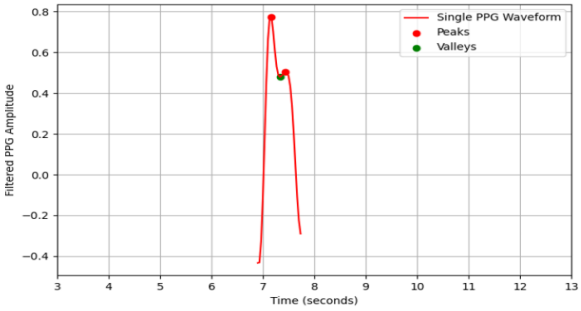
Eq. (5) represents a smoothening operation over a sequence X, producing a new sequence y where each element is the average K−1 value from X, starting from index i+1. As a result, the "peak detection algorithm" generated an array of positive and negative peak values. Fig. 7(b) shows the sample plot of the filtered signal in both color spaces after applying the "peak detection algorithm". A "single PPG wave" with the most prominent "positive systolic peak" was selected from the continuous "PPG waveform" extracted from the "Red" and "Hue channels", as illustrated in Fig. 7(c). The flowchart for extracting a "single PPG wave" is shown in Fig. 8. Thus, a clean "PPG signal" was obtained from the video of the index finger in both "RGB" and "HSV color spaces".




(a)




(b)




(c)

Fig. 7. (a) Filtered PPG signal, (b) Application of peak detection algorithm to PPG wave, (c) Extracted single PPG waveform with highest peak.

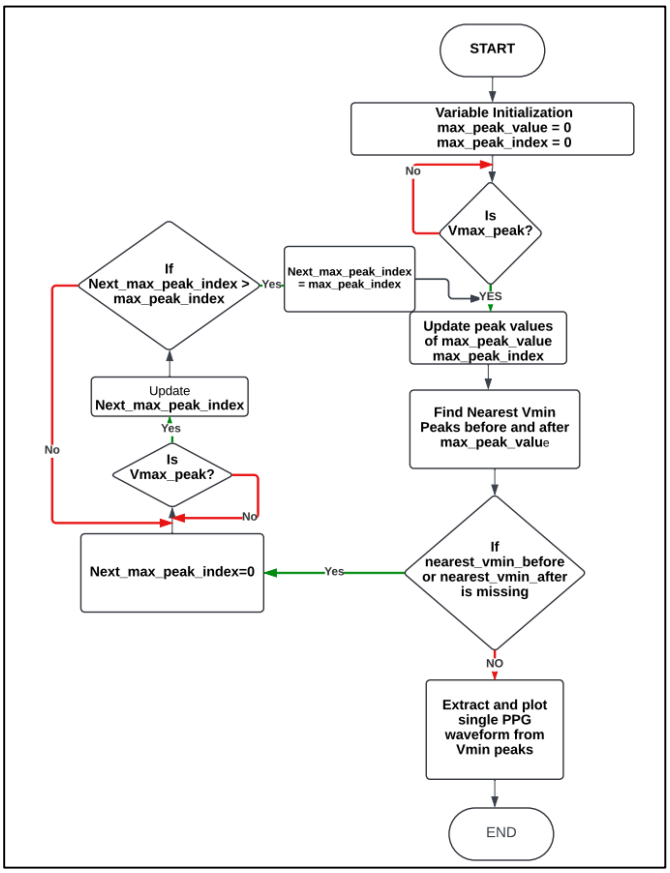



Fig. 8. Flowchart to extract single PPG waveform.

## V. Feature Extraction

Once the PPG waveform with the highest peak was extracted from both color spaces, feature extraction is a critical step, as it has a major impact on the performance and accuracy of predictive models. Fig. 9 illustrates the procedure for collecting 49 distinct features, which were obtained from the subject's information and from the "PPG signal's time and frequency domain" analysis. A total of 21 features (f3 to f22 and f48) were derived from the "PPG signal", 19 features were derived from the "first derivative and second derivative" of the "PPG signal" (f23 to f41), and six features (f42 to f47) were obtained by applying the "Fast Fourier Transform (FFT)" to the PPG waveform for each subject in both the color spaces. The extraction of features from the "PPG wave" and its "derivative" is illustrated in the figure. Additionally, the age (f1), gender (f2), and body mass index (f49) of each subject were incorporated in the feature set. The distinct features obtained from the "PPG signal" and its corresponding "first and second derivatives" are shown in Fig. 10. The extracted features are listed in Table I. The process of extracting features in "RGB" and "HSV color spaces" was identical.

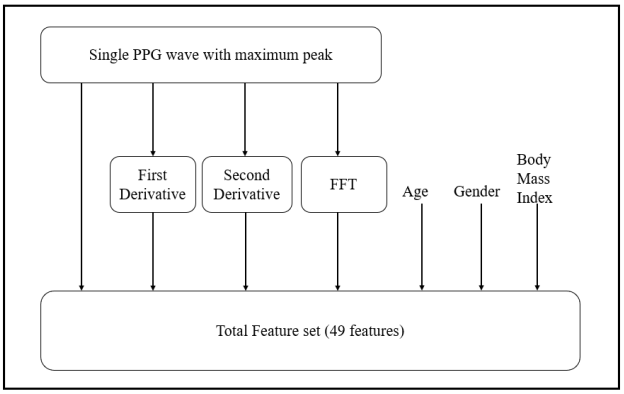



Fig. 9. Schematic diagram of the feature extraction process.

TABLE I. List of Features

| Feature | Description | Feature | Description |
|---|---|---|---|
| f1 | Age | f26 | $t_{f1}$ |
| f2 | Gender | f27 | $b_2/a_2$ |
| f3 | x | f28 | $e_2/a_2$ |
| f4 | y | f29 | $(b_2+e_2)/a_2$ |
| f5 | z | f30 | $t_{a2}$ |
| f6 | TIP | f31 | $t_{b2}$ |
| f7 | y/x | f32 | $t_{a1}/t_{pi}$ |
| f8 | (x-y)/x | f33 | $t_{b1}/t_{pi}$ |
| f9 | z/x | f34 | $t_{e1}/t_{pi}$ |
| f10 | (y-x)/x | f35 | $t_{f1}/t_{pi}$ |
| f11 | $t_1$ | f36 | $t_{a2}/t_{pi}$ |
| f12 | $t_2$ | f37 | $t_{b2}/t_{pi}$ |
| f13 | $t_3$ | f38 | $(t_{a1}+t_{a2})/t_{pi}$ |
| f14 | Δt | f39 | $(t_{b1}+t_{b2})/t_{pi}$ |
| f15 | $t_1/2$ | f40 | $(t_{e1}+t_2)/t_{pi}$ |

| | | | |
|---|---|---|---|
| f16 | $A_2/A_1$ | f41 | $(T_{f1}+t_3)/t_{pi}$ |
| f17 | $t_1/x$ | f42 | $X(f_0)$ |
| f18 | $y/(t_{pi}-t_3)$ | f43 | $\|X(f_0)\|$ |
| f19 | $t_1/t_{pi}$ | f44 | $X(f_1)$ |
| f20 | $t_2/t_{pi}$ | f45 | $\|X(f_1)\|$ |
| f21 | $t_3/t_{pi}$ | f46 | $X(f_2)$ |
| f22 | $\Delta t/t_{pi}$ | f47 | $\|X(f_2)\|$ |
| f23 | $t_{a1}$ | f48 | $v_2/v_1$ |
| f24 | $t_{b1}$ | f49 | BMI |
| f25 | $t_{e1}$ | | |

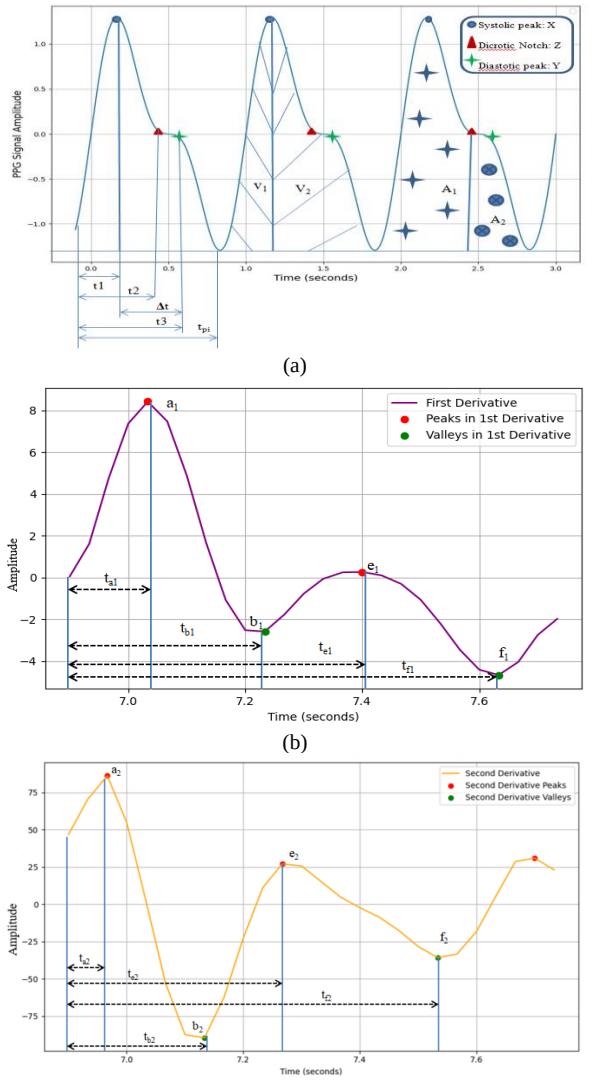



Fig. 10. Feature extraction from (a) Original "PPG wave", (b) "First derivative of PPG wave", and (c) "Second derivative of PPG wave".

## VI. Feature Selection and Model Development

"GA" selected a subset of features from the "Red" and "Hue channels". GA is the feature optimization method inspired by natural evolution. It begins with an initial population of potential solutions (subsets of features), then iteratively selects the best candidates using crossover, mutation, and selection based on a fitness function (such as cross-validation performance). GA is highly effective in feature selection for complex problems where features interact with each other in non-obvious ways. It is especially suited for feature selection in medical datasets as it evolves mathematical expressions to find the optimal feature combination that minimizes prediction errors. The object function is represented mathematically as in Eq. (6).

$$Obj = Min(\mathcal{E}) + \lambda * \quad (6)$$

Where:

$\mathcal{E}$: Error represents the deviation of predicted values from the actual values.

$\lambda$: Regularization parameter controlling the trade-off between accuracy and simplicity.

C: Complexity refers to the overall intricacy of the chosen features.

The "DEAP (Distributed Evolutionary Algorithms in Python) library" is a powerful and flexible framework for implementing evolutionary algorithms such as GA. Feature selection started with all available features, and the process continued through elimination until the optimal outcomes were obtained.. This process aimed to identify the most significant features contributing to the prediction performance of regression models. In this study, different regression models, including "CatBoost", "XGBoost", "RFR", and "Gradient Boosting", were utilized to estimate blood glucose levels, with the features selected through a GA for optimal predictive performance. This study explored various control parameter settings of the GA to enhance accuracy while reducing the number of features. The optimal performance was achieved with "100 generations, a population size of 50, a crossover probability of 0.8, and a mutation probability of 0.1", which successfully identified the most important features for better predictive accuracy. When applied to "RGB" and "HSV color spaces", the number of selected features varies for different regression models.

## VII. Result and Discussion

A total of 234 subjects were participated in the study, with fingertip video data recorded using a smartphone camera and an NIR LED module. For each subject, a 15-second video was captured, initially in the "RGB color space" and then converted to the "HSV color space" for further analysis. Several preprocessing techniques were employed to extract the "PPG wave" from both color spaces. Various "time-domain and frequency-domain" features were extracted from the original "PPG wave" as well as from its "derivatives". Additionally, demographic information such as "age, gender, and BMI" was incorporated as additional features. Several regression models were evaluated for predictive performance, and the XGBoost model demonstrated superior results in both the "RGB and HSV color spaces", highlighting its effectiveness and robustness in accurately estimating the target variable.

The effectiveness of the model was accessed using the $R^2$ score and MAE. $R^2$ and MAE were chosen as performance metrics due to their complementary nature$R^2$ indicates the fraction of variance accounted for by the model, reflecting its

goodness-of-fit, while MAE offers a straightforward measure of prediction accuracy by calculating the average error magnitude, making it resistant to outliers. The assessment metrics are mathematically defined by the Eq. (7) and (8). Furthermore, consistency analysis was performed using "Bland-Altman", "scatter plots", and "Clarke grid analysis". It is worth mentioning that all the results from these analyses were obtained from the 30% test dataset.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{actual} - y_{predicted}\right| \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{actual} - y_{predicted})^2}{\sum_{i=1}^{n}(y_{actual} - y_{mean\_of\_actual})^2} \quad (8)$$

Where, $y_{actual}$: actual blood glucose value,

$y_{predicted}$: predicted blood glucose value,

$y_{mean\_of\_actual}$: mean of actual blood glucose values.

As shown in Table II, "XGBoost", "CatBoost", "RFR", and "Gradient Boosting Regression" algorithms were tested and compared to evaluate their predictive performance for estimating BGL. The GA for feature selection resulted in varying numbers of features being selected across these models, highlighting differences in how each algorithm assessed feature importance and interacted with the selected feature set. These variations can be attributed to model-specific characteristics, such as feature selection criteria, regularization techniques, and sensitivity to over fitting and redundancy. Among the models, "XGBoost" emerged as the top performer, providing the highest R-squared values in "RGB" and "HSV color spaces". "XGBoost" outperformed other models due to its strong regularization capabilities, which prevent over fitting in high-dimensional datasets, and its ability to effectively capture complex, nonlinear relationships and feature interactions. In the "RGB color space", "XGBoost" achieved an $R^2$ value of 0.89 and MAE of 19.89, indicating a strong correlation between predicted and actual BGL, which signifies high predictive accuracy. In the "HSV color space", "XGBoost" delivered an $R^2$ value of 0.84 and MAE of 24.76, demonstrating solid performance, though slightly lower than in RGB.

TABLE II. RESULTS OF MACHINE LEARNING MODELS IN "RGB" AND "HSV COLOR SPACE"

| Color space | Model | Number of features selected | $R^2$ | MAE |
|---|---|---|---|---|
| RGB | XGBoost | 19 | 0.89 | 19.29 |
| | CatBoost | 21 | 0.82 | 23.43 |
| | RFR | 19 | 0.79 | 25.08 |
| | Gradient Boosting | 23 | 0.78 | 30.94 |
| HSV | XGBoost | 27 | 0.84 | 24.76 |
| | CatBoost | 20 | 0.82 | 25.09 |
| | Gradient Boosting | 30 | 0.72 | 27.44 |
| | RFR | 23 | 0.65 | 34.46 |

To evaluate the accuracy of the best-performing "XGBoost model", regression plots, "Clarke grid analysis", and "Bland-Altman plots" were utilized in both color spaces. A regression plot visually illustrates the association between the predictor and response variables in regression analysis. It demonstrates how accurately the model's predictions match the actual data. Fig. 11(a) and (b) illustrates the regression plots for the best-performing "XGBoost model" across the "RGB" and "HSV color spaces". The regression plot revealed a significant association between the predicted and reference BGL values in the "RGB color space", with most data points closely aligned around the regression line, particularly when compared to the "HSV color space".

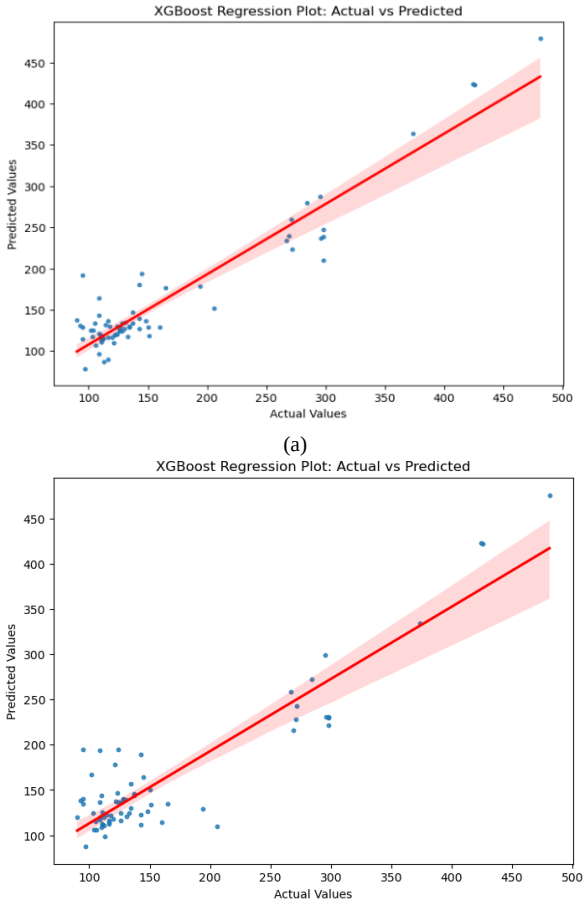
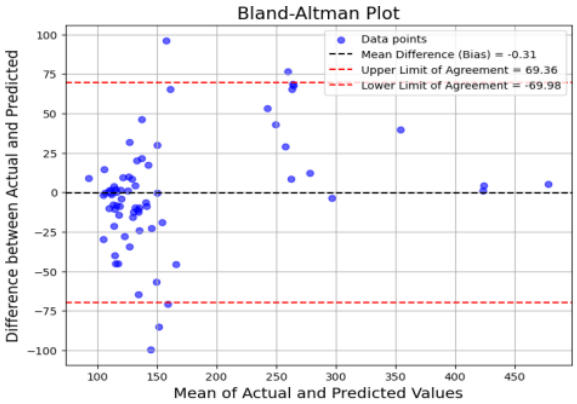



Fig. 11. Regression plot (a) "RGB color space", (b) "HSV color space".

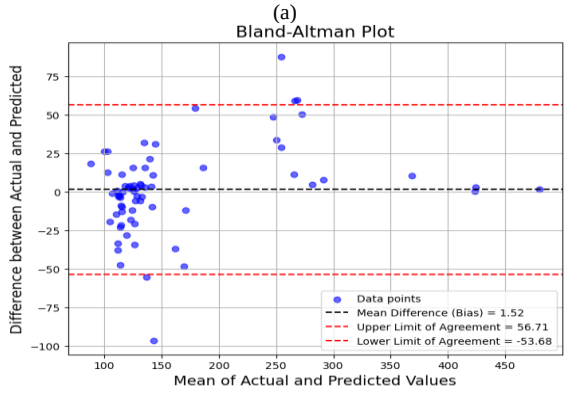
The "Bland-Altman plot" is a visual technique for comparing two measurement techniques. It charts the discrepancies between the methods against their averages, with horizontal lines representing the average difference and the boundaries of agreement, calculated as the average difference ±1.96 times the standard deviation. It was found that only 7.04% of the BGL values fall outside the limits of agreement (±1.96 SD) for the testing dataset in "RGB" and "HSV color spaces", as illustrated in Fig. 12(a) and (b). This demonstrates a high level of agreement between the actual and estimated values.

"Clarke Error Grid Analysis" is widely recognized for validating BGL estimations. The grid is divided into five regions. "Region A" shows predictions within 20% of the actual BGL value. "Region B" includes predictions more than 20% off but not false. "Region C" highlights false positives indicating

incorrect “hypoglycemia” or “hyperglycemia”. “Region D” represents missed “hypoglycemia” or “hyperglycemia” cases, while “Region E” shows errors potentially misclassifying “hypoglycemia” or “hyperglycemia”.



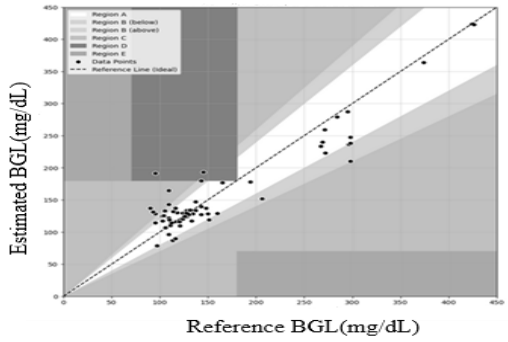

(a)



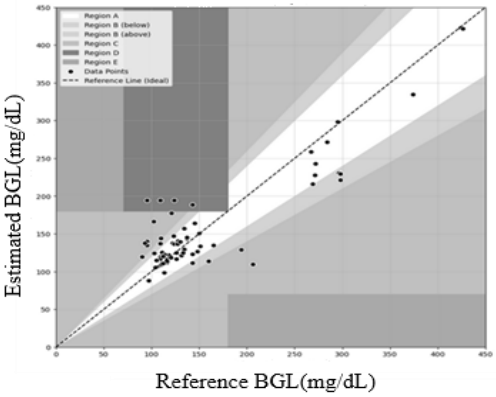

(b)

Fig. 12. Bland Altman plot (a) “RGB color space”, (b) “HSV color space”.

Fig. 13(a) illustrated the distribution of predictions for the “RGB color space”. “Region A” comprised 71.83% of the predictions within 20% of the actual BGL value, and “Region B” represented 19.72% of the predictions. “Region C”, on the other hand, included only 8.45% of the predictions. More than 90% of the data was concentrated in “Regions A and B”, deemed acceptable zones, indicating that most predictions were within a reasonable margin of error from the actual BGL values. Fig. 13(b) showed the prediction distribution for the “HSV color space”, with “Region A” represented 69.01% of predictions within 20% of the actual BGL value and “Region B” accounted for 15.49%. Region C contained 15.49% of false predictions. Around 85% of the predictions were found within “Regions A and B”, suggesting that most predictions were reasonably close to the actual BGL values, with only a tiny portion of the data fell into the false prediction range. In both color spaces, “Regions D and E” contained no data, which suggests that all predictions are confined to the acceptable or marginally acceptable ranges. The results showed that GA effectively selected relevant features for the “Red channel” in the “RGB color space” and the “Hue channel” in the “HSV color space”. While the “Red channel” provided a higher $R^2$ score, the “Hue channel” still performed well.




(a)




(b)

Fig. 13. Clarke Error Grid analysis for (a) “RGB color space”, (b) “HSV color space”.

Table III presented a comparative analysis between the proposed method and several existing contact and non-contact video-based blood glucose level (BGL) estimation approaches. Notably, all previous methods listed in the table performed BGL estimation exclusively within the RGB color space. In contrast, the proposed method explored additional spectral domains beyond RGB, offering a distinct approach to video-based BGL estimation.

By independently analyzing both color spaces, this study provided a detailed exploration of the unique contributions of the RGB and HSV color spaces in feature extraction and BGL estimation performance. The RGB color space achieved an $R^2$ value of 0.89, indicating good predictive accuracy under controlled settings, whereas the HSV color space yielded an $R^2$ value of 0.84, demonstrating strong performance despite being slightly lower. This difference suggested that while the “RGB color space” was effective in scenarios with stable lighting, the “HSV color space” offered better adaptability in more variable real-world conditions.

The dual analysis of “RGB” and “HSV color spaces” provided practical insights for the design of future non-invasive glucose monitoring systems. Depending on specific environmental conditions, device compatibility, and required robustness, researchers could make informed decisions on the most suitable color space to optimize estimation accuracy and reliability.

TABLE III. COMPARISON OF PROPOSED METHOD WITH SEVERAL EXISTING VIDEO BASED BLOOD GLUCOSE ESTIMATION METHODS

| Reference | Device | Color Space | Number of Subjects | Algorithms | Results |
|---|---|---|---|---|---|
| Golap et al. [16] | Nexus- 6p | RGB | 111 | MGGP | $R^2$=0.88 |
| Haque et al. [17] | Nexus- 6p | RGB | 93 | DNN | $R^2$=0.90 |
| Islam et al. [22] | OnePlus 6T | RGB | 52 | PLS | standard error of prediction (SEP) =17.02 mg/dL |
| Nie et al. [25] | Medviv MV-NIR30-A industrial Near Infrared camera | RGB | 8 | RFR | $R^2$=0.60 |
| Proposed work | Samsung A51 | RGB<br>HSV | 234 | XGBoost | $R^2$=0.89<br>$R^2$=0.84 |

## VIII. CONCLUSION

A noninvasive BGL prediction model is proposed based on fingertip video data recorded using a smartphone in both "RGB" and "HSV color spaces". The GA is applied for feature selection in the "Red" and "Hue channels". "XGBoost" performed the best, achieving an $R^2$ value of 0.89 in the "RGB color space" and 0.84 in the "HSV color space". Bland-Altman analysis revealed that only 7.04% of BGL values fell outside the agreement limits for both color spaces. Even though the proposed method demonstrated superior performance on the collected data samples, its generalization is limited due to the relatively small dataset size. Additionally, the dataset did not include data from children under 18 or pregnant women, which restricts the applicability of the results to these specific populations. All data were collected using a single smartphone model (Samsung A51), which may impact the generalizability of the approach across different camera hardware. The experiments were conducted in controlled indoor environments, and as such, the model's performance in real-world conditions—where lighting and background variability are more pronounced—remains to be validated. Furthermore, the participant pool was limited, potentially affecting the model's robustness across diverse demographic groups. The study also focused solely on RGB and HSV color spaces, without exploring other potentially valuable color models.

In the future, efforts should focus on addressing these limitations by expanding the dataset to include more diverse populations and varying environmental conditions. Investigating and implementing innovative approaches to improve both the accuracy and efficiency of the system will also be a key direction. In particular, exploring alternative color spaces and their combinations may help capture more detailed and precise color information. Identifying optimal configurations could lead to better estimation results while reducing computational complexity. Additionally, incorporating advanced feature optimization techniques and a broader set of regression models could further enhance the accuracy and reliability of BGL estimation, ultimately contributing to the development of more robust and scalable non-invasive monitoring systems.

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# Machine Learning Advances in Technology Applications: Cultural Heritage Tourism Trends in Experience Design

Meihua Deng
School of International Communication, Hunan Mass Media Vocational and Technical College, Changsha 410100, Hunan, China

***Abstract*—This study investigates the evolving trends in cultural heritage tourism experience design and examines how machine learning technologies are being applied to enhance visitor engagement and heritage preservation. Using bibliometric data from the Web of Science (WoS) and visualization tools such as VOSviewer, the research identifies key themes, author collaborations, and keyword clusters from 2016 to 2025. The analysis reveals a shift in focus from traditional conservation and display methods to user-centered experiences supported by advanced technologies. Machine learning techniques—such as deep learning, natural language processing, and multimodal data fusion—are increasingly used to personalize tours, analyze tourist behavior, restore damaged artifacts, and improve decision-making in resource management. Tools like CNNs and BERT models enable smart guiding systems and interactive Q&A features, while sentiment analysis enhances feedback mechanisms. The study also highlights several ongoing challenges, including data privacy issues, algorithmic bias, and unequal access to technological infrastructure, especially in developing regions. Ethical considerations and the need for human-centered design principles are emphasized to ensure that technological innovation aligns with cultural values and sustainability goals. In conclusion, this research provides a comprehensive overview of academic progress in cultural heritage tourism and illustrates the growing importance of AI and machine learning in creating immersive, efficient, and culturally respectful tourism experiences. The findings offer practical insights for scholars, heritage site managers, and policymakers seeking to leverage digital tools for both preservation and enhanced visitor satisfaction.**

***Keyword*—*Heritage tourism; tourism experience; machine learning; VOSviewer; bibliometric data***

## I. Introduction

Driven by both globalization and digitization, tourism has gradually become an important link between history and modernity, and between preservation and dissemination. Cultural heritage is not only a carrier of national memory but also an important resource for cultural identity and sustainable development in contemporary society [1]. However, with the rapid growth of tourism demand, it has become a common challenge for both academia and industry practice to provide tourists with both in-depth and interesting experiences under the premise of preserving the authenticity of tourism heritage [2]. Traditional display methods such as static exhibits and one-way explanations have made it difficult to meet tourists' needs for interactivity, personalization, and immersion, while the rise of artificial intelligence (AI) and machine learning technologies has injected new vitality into this field [3]. Through natural language processing, computer vision, data mining, and other technologies, machine learning can not only optimize the analysis of visitor behavior and resource management, but also promote digital preservation and innovative displays, and even reconfigure the interaction mode between visitors and culture.

The paradox of cultural heritage tourism lies in the balance between conservation and utilization. The fragility of tourism resources requires strict environmental control and physical protection; in addition, tourism development needs to attract public participation to realize its social value [4]. Traditional means such as interactive screens in physical museums or simple virtual reality (VR) experiences, although enhancing the sense of participation to a certain extent, still face problems such as homogenization of content and insufficient technical adaptability [5]. Some VR devices cause users to experience a sense of vertigo due to technical limitations, while AR applications often lack long-term appeal due to single content [6]. In recent years, breakthroughs in machine learning technology have provided a new path to solve these problems. Image recognition technology based on deep learning can carry out high-precision classification and repair of cultural relics, and natural language processing technology can realize personalized guided tours through intelligent question-and-answer systems, and even optimize the feedback mechanism for tourists by combining sentiment analysis [7]. The application of these technologies not only enhances the intelligent level of experience but also through data-driven dynamic adjustment.

At the theoretical level, this study integrates the multidisciplinary perspectives of heritage, tourism management, and computer science to build a trinity analytical framework of "technology-experience-protection", which makes up for the insufficiency of the existing literature that separates the application of technology and humanistic care [8]. The application of Laboratory Information Management System (LIMS) in heritage monitoring not only improves data management efficiency but also realizes preventive protection through environmental sensors and early warning mechanisms, reflecting the dual value of technological empowerment and cultural sustainability. At the practical level, the research

findings can provide operable technical solutions for scenic spots [9]. Visitor evaluation models based on sentiment analysis can help managers identify service shortcomings, while multimodal data fusion techniques (e.g., combining image and text data) can assess the quality of experience more comprehensively. In addition, the case studies show that the successful application of AI technologies needs to be based on cross-disciplinary cooperation.

To systematically explore these topics, this paper is organized as follows: Section II provides a comprehensive review of existing literature on cultural heritage tourism and the integration of machine learning technologies. Section III details the methodology, including data collection strategies and the analytical framework used. Section IV presents the findings derived from bibliometric and visual analyses, supported by relevant case studies. Finally, Section V discusses the conclusions drawn from the research, outlines practical implications, and proposes directions for future studies.

## II. Research Review

### A. Overview of Cultural Heritage Tourism Research

Cultural heritage tourism is developing rapidly, driven by globalization and digitization. Its core objective is to realize cultural dissemination, education, and social value through the interaction between tourists and tourism resources [10]. This model of tourism not only emphasizes cultural and educational aspects, but also focuses on tourists' sense of participation and immersion, and seeks to find a balance between conservation and development [11]. In recent years, with the diversification of tourism needs and technological advances, related research has gradually shifted from traditional conservation and display to focus on visitor experience and technological innovation. In terms of the definition and characteristics of tourism, scholars generally agree that its uniqueness lies in the combination of culture, education, experience, and sustainability [12]. Cultural heritage tourism is not only an economic activity but also a means of cultural dissemination and education. In recent years, research hotspots have focused on visitor experience optimization, digital preservation, community participation and cultural identity, and tourism impact assessment [13]. The application of virtual reality (VR) and augmented reality (AR) technologies has provided visitors with immersive experiences, but how to avoid "de-culturalization" caused by the misuse of technology remains a challenge. The digitization project of the Mogao Grottoes in Dunhuang has reduced the loss of physical artifacts and provided visitors with a richer experience through high-precision scanning and virtual reconstruction [14]. In addition, the importance of community participation in heritage tourism is becoming more and more evident. In Japan, Shirakawa-go Hapo Village has successfully preserved its traditional architecture and culture through community-led tourism development [15]. However, related tourism resources still face challenges such as the contradiction between conservation and development, the limitations of technology application, and the conflict between globalization and localization. Over-commercialization may lead to "westernization" and weaken its cultural value, while misuse of technology may lead to "dehumanization" of the cultural experience.

In the future, research related to tourism will pay more attention to multidisciplinary integration and technological innovation. Optimizing tourists' behavior prediction and resource management through artificial intelligence and big data analysis, or realizing digital rights and protection through blockchain technology will become important directions [16]. At the same time, research should also pay attention to cultural ethics and community participation, and explore the path of "people-centered" sustainable development [17]. All in all, the research in this field not only provides rich theoretical perspectives for academics but also provides important guidance for conservation and development in industry practice.

### B. Review of Machine Learning Research

Machine learning, as one of the core technologies of artificial intelligence, has shown great potential in the field of tourism in recent years. Its core lies in the algorithmic model to learn the laws from the data and use them for prediction, classification, and decision-making [18]. Machine learning is mainly divided into three categories: supervised learning, unsupervised learning, and reinforcement learning, in which supervised learning trains models through labeled data, unsupervised learning discovers potential laws from unlabeled data, and reinforcement learning optimizes decision-making through trial-and-error and reward mechanisms. Deep learning, as an important branch of machine learning, processes complex data through multi-layer neural networks and shows unique advantages in cultural heritage tourism [19]. Convolutional neural networks (CNN) can be used for cultural relics image classification and restoration, while recurrent neural networks (RNN) are suitable for tourists' behavior sequence analysis. The application of machine learning mainly focuses on the analysis and prediction of tourists' behavior, intelligent guiding and interactive experience, as well as resource management and decision support [20]. By analyzing tourists' browsing trajectories, consumption records, and comment data, machine learning can identify tourists' preferences and behavioral patterns and provide tourists with personalized tour routes. In terms of digital protection, machine learning uses deep learning algorithms to virtually repair damaged cultural relics, or automatically classify and label cultural relics using image recognition technology. Natural Language Processing (NLP) technology provides support for the intelligent tour system, and the NLP-based intelligent Q&A system can answer visitors' questions in real-time and enhance the interactive experience. In addition, the application of machine learning in scenic resource scheduling and risk assessment is gradually maturing, predicting visitor flow through time series analysis, or identifying safety hazards using anomaly detection algorithms.

However, the application of machine learning in tourism still faces many challenges. Data quality and privacy are the first obstacles, as data in the tourism sector is often noisy and missing, and the privacy protection of tourists' data is also an urgent issue to be solved. Algorithmic bias and interpretive issues should also not be ignored [21]. Recommender systems based on historical data may reinforce tourists' inherent preferences, limiting the experience of cultural diversity, while the "black-box" nature of deep-learning models makes it difficult to explain their decision-making process, affecting user trust. In addition, the application of machine learning

technology requires high hardware and software investment, which limits its popularization in small and medium-sized scenic spots.

The application of machine learning in tourism will focus more on multimodal data fusion and interdisciplinary cooperation. Combining image, text, and sensor data to build a more comprehensive analysis model of tourist behavior. At the same time, research should also pay attention to technical ethics and user experience, and explore the "human-centered" technology adaptation path [22]. In conclusion, machine learning provides a new technical tool and research paradigm for tourism, but its successful application should be based on data quality, algorithmic fairness, and user needs, and seek a balance between technological innovation and humanistic values.

## III. Methodology

### A. Data Collection

In this study, the Web of Science (WoS) database was used as the data source, and VOSviewer software was used to visualize and analyze the literature data to reveal the research trends and hotspots in the field of cultural heritage tourism experience design. First, the WoS database was searched with keywords such as "cultural heritage" and "tourism" to filter out high-quality literature related to the topic, spanning from 2016 to 2025. By setting the type of literature as "Article" and "Review", and excluding the literature not related to the topic, we finally obtained an effective literature data set.

In the data pre-processing stage, the title, abstract, keywords and other information of the literature are cleaned and standardized, and the expression form of keywords is unified (e.g., "VR" and "virtual reality" are merged) to ensure the accuracy of the analysis. Subsequently, the processed data were imported into VOSviewer software, and its powerful network visualization function was used to construct the keyword co-occurrence network, author cooperation network, and literature co-citation network [23]. In the keyword co-occurrence analysis, high-frequency keywords were screened out by setting the minimum occurrence frequency threshold, and cluster maps were generated to visualize the research hotspots and their relevance [24]. In author collaboration network analysis, the core research power in the field is revealed by identifying high-output authors and their collaboration teams. In addition, literature co-citation analysis is used to identify high-impact literature and its research themes to further explore the knowledge base and evolution path in the field.

Through the visual analysis of VOSviewer, this study can not only identify the research hotspots in the field of cultural heritage tourism experience design (e.g., "digital preservation", "visitor experience optimization", "community participation", etc.) but also reveal the correlation between different research themes and their trends over time. This study not only identifies the research hotspots in the field of cultural heritage tourism experience design (e.g. "digital preservation", "tourist experience optimization", "community participation", etc.) but also reveals the correlation between different research themes and their trends over time. While early studies focused on the application of technological tools, in recent years more attention has been paid to user experience and sustainability. This visualization method provides an important literature base and theoretical support for subsequent research on the application of machine learning techniques.

### B. Research Methods in Machine Learning

In the research method section of machine learning, this study adopts a data-driven approach, combining with the actual needs of the tourism field, to design and implement a series of machine learning models to optimize the design and protection of the tourist experience. First, data collection and preprocessing are the basis of machine learning research [25]. This study obtains data from multiple sources, including literature data in the WoS database, visitor behavior data (browsing trajectory, comment data) from cultural heritage scenic spots, and digitized data (images of cultural relics, 3D models) from tourism resources. High-quality training datasets are constructed through data cleaning, feature extraction, and normalization.

In the model selection and training phase, this study uses a variety of machine learning algorithms according to the specific task requirements. In the task of tourist behavior analysis and prediction, supervised learning algorithms (Random Forest, Support Vector Machine) are used to classify and regressively analyze tourists' preferences and behavioral patterns; in the task of digital protection of cultural heritage, deep learning algorithms (Convolutional Neural Networks CNN) are used to automatically classify and repair cultural relics images; and in the task of intelligent tour guiding and interactive experience, the natural language processing technology (BERT model) is used to construct an intelligent Q&A system to realize personalized tour guiding [26]. BERT model is used to build an intelligent Q&A system and realize personalized tours [27]. In addition, this study also tries to apply reinforcement learning to scenic resource scheduling, optimizing the visitor experience by dynamically adjusting the distribution of people flow. Among them, are the machine learning methods in the basic class, as shown in Table I.

In the model evaluation and optimization stage, cross-validation, confusion matrix, and ROC curve are used to evaluate the model performance, and the model precision is further improved by hyperparameter tuning and feature selection. In the tourist satisfaction prediction task, the optimal model is selected by comparing the accuracy and recall of different algorithms. Meanwhile, this study also focuses on the interpretability of the model and utilizes methods such as Shapley Additive Explanations (SHAP) values to explain the model decision-making process to enhance user trust. Among the machine learning methods in the application category, as shown in Table II.

TABLE I. MACHINE LEARNING METHODS FOR THE BASE CLASS

| Research Methodology | Specific Techniques/Algorithms | Application Scenario | Data Sources | Assessment of Indicators |
|---|---|---|---|---|
| Supervised learning | Random Forest | Tourist behavior classification (e.g., preference analysis, satisfaction prediction) | Visitor comment data, browsing track data | Accuracy, Recall, F1 Score |
| | Support Vector Machines (SVM) | Tourist flow forecasts, scenic area resource demand forecasts | Historical visitor data, scenic area operation data | Mean Square Error (MSE), $R^2$ value |
| | Logistic Regression | Visitor satisfaction dichotomy (satisfied/dissatisfied) | Visitor questionnaire data | ROC curves, AUC values |
| unsupervised learning | K-means Clustering (K-means Clustering) | Clustering of tourist behavior patterns (e.g., high-spending groups, cultural preference groups) | Tourist consumption data, behavioral track data | Silhouette Score |
| | Principal Component Analysis (PCA) | Data dimensionality reduction and feature extraction for visitor behavior analysis | Multi-dimensional visitor data | Explained Variance Ratio (EVR) |
| deep learning | Convolutional Neural Network (CNN) | Classification and Restoration of Cultural Heritage Images | Artifact image data, 3D scanning data | Classification accuracy, image reconstruction error |
| | Recurrent Neural Networks (RNN) | Visitor behavior sequence analysis (e.g., browsing path prediction) | Visitor track data | Sequence prediction accuracy, loss function value |
| | Long Short-Term Memory Network (LSTM) | Tourist flow time series forecasting | Historical Visitor Traffic Data | Mean Square Error (MSE), Mean Absolute Error (MAE) |

TABLE II. MACHINE LEARNING METHODS FOR APPLICATION CLASS

| *Research Methodology* | *Specific techniques/algorithms* | *Application scenario* | *Data sources* | *Assessment of indicators* |
|---|---|---|---|---|
| Natural Language Processing (NLP) | BERT model | Intelligent Q&A system, visitor comment sentiment analysis | Visitor comment data, cultural heritage interpretation texts | Accuracy, F1 scores, BLEU scores (Q&A system) |
| | TF-IDF + Sentiment Analysis | Theme Extraction and Sentiment Tendency Analysis of Visitor Comments | Visitor comment data | Sentiment classification accuracy, subject coverage |
| Model Interpretive Approach | SHAP values (Shapley Additive Explanations) | Explaining the decision-making process in predictive models of tourist behavior | Model Output and Feature Data | Feature Importance Ranking, Interpretive Consistency |
| | LIME (Local Interpretable Model-agnostic Explanations) | Localized interpretation of model predictions (e.g., satisfaction predictions) | Model output with local feature data | Interpretation stability, local fit |
| Multimodal data fusion | Image+ Text fusion model (e.g. CLIP) | Multimodal analysis combining images of artifacts with explanatory texts | Cultural heritage image data, explanatory text data | Multimodal classification accuracy, feature alignment effect |
| | Sensor Data+ Behavioral Data Fusion | Integrated analysis of visitor behavior and environmental data (e.g., impact of temperature and humidity on visitor experience) | Environmental sensor data, visitor behavior data | Data fusion effect, model prediction accuracy |

Finally, this study combines the practical application effect of the machine learning model with the practical needs of tourism and verifies its feasibility and effectiveness through case studies. In conclusion, through the data-driven machine learning research method, this study not only provides new technical tools for cultural heritage tourism experience design but also provides an important reference for technical landing and optimization in the industry practice.

## IV. FINDINGS AND DISCUSSION

### A. Visual Analysis of Authors

The authors' visualization analysis is obtained by using "tourism" and "machine learning" as keywords on WOS and using VOS software. Fig. 1, shows a visual graph generated by VOSviewer, which shows the collaboration network of related authors under the themes of "tourism" and "machine learning". The position and size of the nodes in the graph reflect the authors' research impact and collaboration intensity, while the lines between the nodes indicate the collaboration relationship between the authors [28]. From the Fig. 1, it can be seen that some authors have larger nodes, indicating that their research results in this field are more prominent and their cooperation with other authors is more intense. Some scholars have larger nodes and more connected lines, indicating that they are more active in collaborative research in the field of machine learning and tourism. In addition, the graph shows some smaller nodes of authors who may have less research output or less collaboration in the field but are still part of the research network [29]. Overall, this map reveals the core research strengths and their collaboration patterns in the field of machine learning and tourism, providing an important reference for subsequent research.

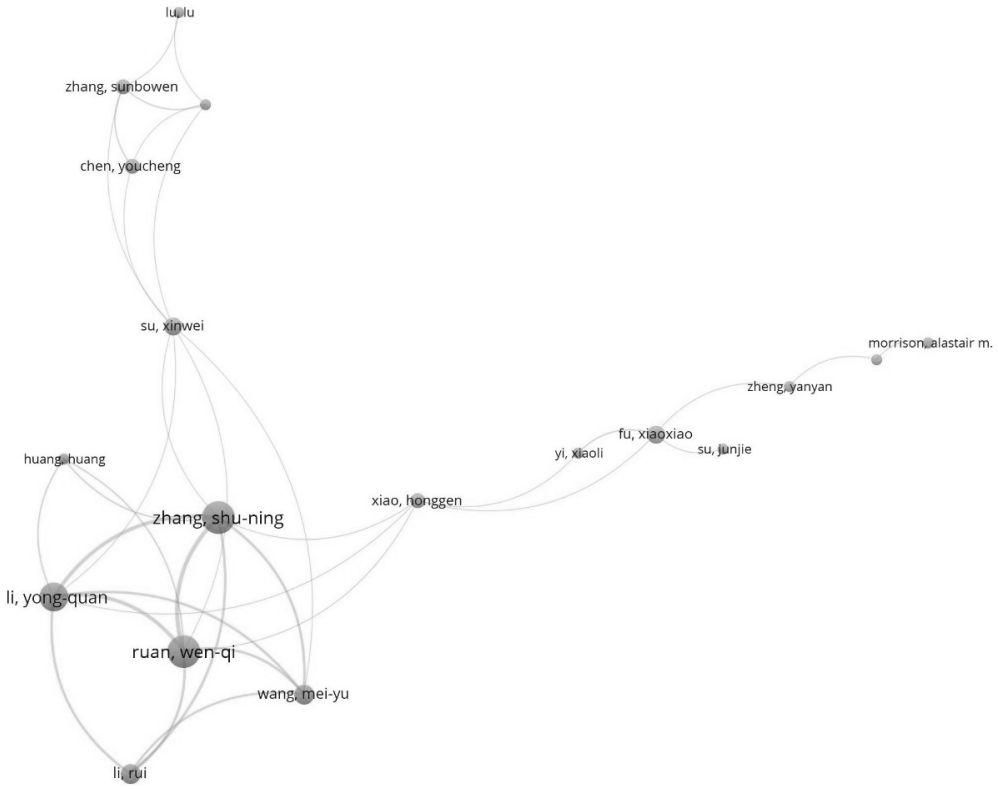


Fig. 1. Author's visualization.

Table III further refines the results of the VOSviewer analysis by listing the relevant authors' documents, citations, and total link strength under the themes of "tourism" and "machine learning". The results of the study are listed as documents, citations, and total link strength under the themes of "tourism" and "machine learning". From the data, Ruan Wen-Qi and Zhang Shu-Ning have the most prominent research results, with 11 documents and 97 citations respectively, and their collaboration strength is 31, indicating that their research in this field has a greater influence and close cooperation. Some scholars' research results are also more significant, with 9 and 5 documents, 75 and 60 citations, respectively, and 29 and 20 intensity of cooperation, respectively. In addition, some scholars' research results are fewer (all 4 documents), but the number of citations is 54 and 35, respectively, indicating that the quality of their research is higher [30]. Overall, the document data further validates the visualization results in the picture, reveals the core authors and their research impact in the field of machine learning and tourism, and provides an important literature base for subsequent research.

TABLE III. FURTHER REFINEMENT OF VOS VIEWER ANALYSIS RESULTS

| *Id* | *Author* | *Documents* | *Citations* | *Total link strength* |
|---|---|---|---|---|
| 46 | al-ANSI, amr | 4 | 36 | 0 |
| 772 | fu, Xiao Xiao | 4 | 54 | 0 |
| 1288 | Lee, Timothy J. | 4 | 65 | 0 |
| 1333 | Li, Rui | 5 | 52 | 19 |
| 1348 | Li, Yong-Quan | 9 | 75 | 29 |
| 1587 | Mishra, Smriti | 5 | 22 | 5 |
| 1655 | Nag, Aditi | 5 | 22 | 5 |
| 1987 | Ruan, Wen-Qi | 11 | 97 | 31 |
| 2224 | Su, Xinwei | 4 | 35 | 4 |
| 2303 | Timothy, Dallen J. | 4 | 21 | 0 |
| 2409 | Wall, Geoffrey | 4 | 38 | 0 |
| 2428 | Wang, Mei-Yu | 5 | 60 | 20 |
| 2652 | Zhang, Mu | 4 | 121 | 0 |
| 2660 | Zhang, Shu-Ning | 11 | 97 | 31 |

Combined with the results of the charts, the following conclusions can be drawn: under the themes of "tourism" and "machine learning", some of the authors are the core researchers in the field, with rich and highly cited research outputs, and close collaborative networks. Some authors are the core researchers in this field, with rich research results, high citation counts, and close collaborative networks [31]. The research direction of these authors may cover multiple application scenarios of machine learning in tourism, such as tourist behavior analysis, intelligent recommendation systems, and so on. In addition, although some authors have fewer research results, the quality of their research is higher, indicating that their research in this field has high academic value. Overall, the results of these analyses provide important literature support and collaborative references for subsequent research in the field of machine learning and tourism [32]. Further analysis of the research directions of these core authors reveals that their applications in the field of machine learning and tourism are mainly focused on the following aspects: firstly, tourists' behavior analysis and prediction is one of the hotspots of the research, and tourists' browsing trajectories, consumption records, and other data can be analyzed by machine learning algorithms, which can identify the tourists' preferences and behavioral patterns, and thus provide decision-making support for scenic spot management [33]. Secondly, an intelligent recommendation system is also an important research direction, through collaborative filtering algorithms or deep learning models, it can provide tourists with personalized travel route recommendations, and enhance the satisfaction and experience of tourists.

### *B. Visualization and Analysis of Cultural Heritage and Tourism*

The visual analysis of cultural heritage and tourism is obtained by using "tourism" and "cultural heritage" as keywords on WOS and using VOS software. In Table IV, the keywords related to cultural heritage tourism, their occurrences, and total link strength are listed, which reflect the research hotspots and their relevance in this field.

"Tourism" and "cultural heritage" are the most frequent keywords, 271 and 225 times respectively, and the total link strength is 431 and 304 respectively, which indicates that "tourism" and "cultural heritage" are the core research themes in this field, and the correlation between them is very strong. Other high-frequency keywords such as "heritage tourism" (99 times), "cultural tourism" (158 times) and "heritage" (158 times). “Heritage" (heritage, 140 times) further confirms the centrality of this keyword research. The high frequency of these keywords suggests that research on this tourism model focuses not only on the preservation and presentation of its heritage but also on its integration with tourism activities to achieve the dual goals of cultural dissemination and economic development. The keywords also listed in Table IV reveal several research hotspots in the field of this mode of tourism. "Authenticity" (99 times) and "intangible cultural heritage" (64 times) reflect researchers' concern for the authenticity of heritage and intangible cultural preservation. Culture protection; "sustainability" (68 times) and "sustainable tourism" (70 times) indicate that sustainability is an important direction for tourism research in this mode. In addition, the keywords "management" (103 times) and "impact" (41 times) reveal that the management and impact assessment of this mode of tourism is also one of the hot spots of research [34]. The high frequency of these keywords indicates that the research on this mode of tourism not only focuses on the protection and display of cultural heritage but also on its integration with tourism activities to achieve the dual goals of cultural dissemination and economic development.

TABLE IV. VISUAL MAPPING OF "TOURISM" AND "CULTURAL HERITAGE"

| *Id* | *Keyword* | *Occurrences* | *Total link strength* |
|---|---|---|---|
| 204 | authenticity | 99 | 243 |
| 378 | China | 40 | 78 |
| 527 | conservation | 68 | 161 |
| 687 | cultural heritage | 225 | 304 |
| 770 | cultural tourism | 158 | 246 |
| 798 | cultural-heritage | 76 | 182 |
| 1122 | experience | 44 | 85 |
| 1360 | Heritage | 140 | 233 |
| 1416 | Heritage tourism | 99 | 185 |
| 1534 | identity | 43 | 87 |
| 1557 | impact | 41 | 96 |
| 1632 | intangible cultural heritage | 64 | 113 |
| 1911 | management | 103 | 249 |
| 2029 | model | 55 | 117 |
| 2316 | perceptions | 51 | 124 |
| 2740 | satisfaction | 68 | 145 |
| 2842 | sites | 45 | 128 |
| 3055 | sustainability | 68 | 165 |
| 3065 | sustainable development | 47 | 91 |
| 3090 | sustainable tourism | 70 | 118 |
| 3196 | tourism | 271 | 431 |
| 3652 | world heritage | 43 | 97 |

The total link strength reflects the relevance of the keywords. The high link strength between "cultural heritage" and "tourism" (304 vs. 431) indicates a strong association between the two in the study. In addition, the link strength between "heritage tourism" and "cultural tourism" is also high (185 vs. 246), indicating that these two forms of tourism are often discussed side by side in research. The strength of links between other keywords such as "authenticity" and "sustainability" (243 vs. 165) suggests that authenticity and sustainability of cultural heritage are also often discussed together in research. These linkage analyses reveal that the study is not a simple one. These linkage analyses reveal the multidimensional character of this model of tourism research, i.e., researchers are not only concerned with the preservation and presentation of heritage but also with its integration with tourism activities to achieve the dual goals of cultural dissemination and economic development. The occurrence of the keyword "China" (China, 40 times) indicates that China occupies an important position in related tourism research. This

may be related to China's rich cultural heritage resources and its need for cultural dissemination in the context of globalization. In addition, the occurrence of "world heritage" (world heritage, 43 times) indicates that the protection and tourism development of world heritage sites are also important directions of research. The occurrence of these keywords reflects the globalization feature of related tourism research, i.e., researchers not only focus on the heritage of a specific region but also heritage conservation and tourism development on a global scale. The occurrence of the keywords "experience" (44 times) and "satisfaction" (68 times) indicates that tourist experience and satisfaction are important directions in tourism research. By analyzing tourists' experience and satisfaction, the researchers explore how to improve the quality and attractiveness of cultural heritage tourism. The immersion of tourists is enhanced through virtual reality (VR) technology or the engagement of tourists is enhanced through intelligent guiding systems [35]. The emergence of these keywords indicates that research on cultural heritage tourism not only focuses on the protection and display of heritage but also on tourists' experience and satisfaction, to realize the dual goals of cultural dissemination and economic development.

Fig. 2 shows the keyword density map generated based on VOSviewer, which reflects the distribution density and importance of each keyword in the research under the themes of "tourism" and "cultural heritage". The color of the density map indicates the degree of concentration of the keywords, and the darker the color, the higher the frequency of the keywords in the study, and the greater the heat of the study [36]. As can be seen from the graph, "tourism" and "cultural heritage" are the keywords with the highest density and the darkest color, indicating that they are the core themes of the study. Other high-density keywords such as "heritage tourism", "sustainability" and "authenticity" also show a high density of keywords. The "authenticity" also shows high research intensity. The high-density distribution of these keywords indicates that tourism-related research not only focuses on the preservation and display of tourism heritage but also its integration with tourism activities to realize the dual goals of cultural dissemination and economic development [37]. In addition, the density of keywords such as "community", "experience" and "satisfaction" is also high, indicating that the tourism research is not only concerned with the preservation and display of tourism heritage but also focuses on its integration with tourism activities to achieve the dual goals of cultural dissemination and economic development. ) also have a high density, indicating that community participation, tourist experience, and satisfaction are important directions for research.

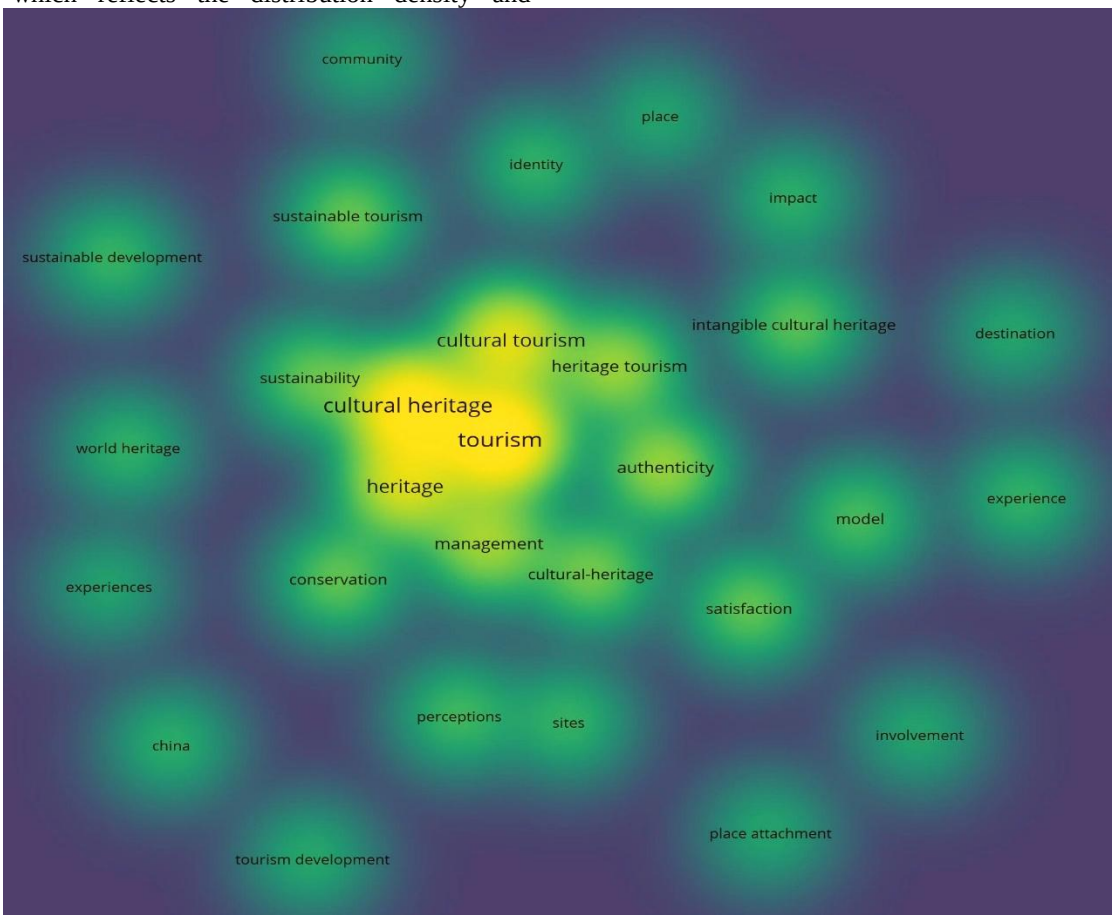


Fig. 2. Density mapping of cultural heritage and tourism.

Fig. 3 is a keyword clustering diagram generated based on VOSviewer, reflecting the correlation between keywords and their clustering characteristics under the themes of "tourism" and "cultural heritage". Different colors in the clustering diagram indicate different research themes or directions, and keywords within the same color have a strong correlation. From

the figure, it can be seen that the keywords are categorized into multiple clusters, and each cluster represents a research topic or direction. For example, the red cluster may represent "cultural heritage conservation and sustainability", including keywords such as "conservation", "sustainability" and "sustainability", “(conservation)”, "sustainability" and "sustainable development". The green cluster might represent "visitor experience and satisfaction", including keywords such as "experience", "satisfaction" and "sustainability", “satisfaction" and "perceptions". The blue cluster may represent "community engagement and place attachment", including keywords such as "community", "identity" and "place attachment". These clusters reveal the multidimensional character of tourism research, i.e., researchers not only focus on heritage preservation and display but also tourists' experience and satisfaction, community participation, and place attachment [38]. For example, the keywords in the red clusters reflect the importance of cultural resource conservation and sustainable development, while the keywords in the green clusters reveal the centrality of tourist experience and satisfaction in cultural resource tourism.

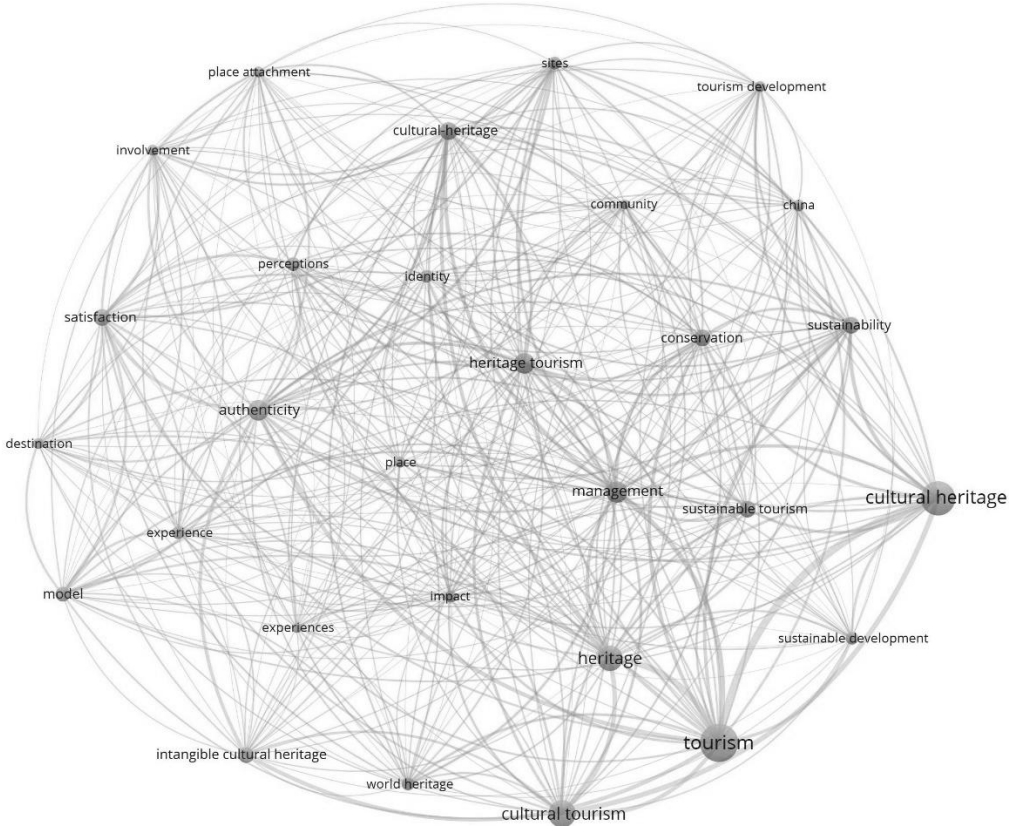


Fig. 3. Basic clustering map of cultural heritage and tourism.

### *C. Machine Learning and Visual Analytics for Tourism*

The visual analysis of machine learning and tourism is obtained by using "tourism" and "machine learning" as keywords on WOS and using VOS software. The keywords related to the application of machine learning in tourism, their occurrences, and total link strength are listed in Table V and Table VI, which reflect the research hotspots and their relevance in this field.

From Table V and Table VI, it can be seen that "machine learning" and "tourism" are the keywords with the highest frequency of 282 and 147 times respectively, and the total link strength is 433 and 285 respectively. This indicates that "machine learning" and "tourism" are the core research topics in this field, and the correlation between them is very strong. Other high-frequency keywords such as "big data" (58 times), "sentiment analysis" (61 times) and "artificial intelligence" (61 times) are also used. “Intelligence" (artificial intelligence, 42 times) further confirms the wide application of machine learning in the field of tourism. The high frequency of these keywords indicates that the application of machine learning techniques in tourism research is not only limited to the traditional analysis of tourists' behaviors but also covers a variety of aspects such as sentiment analysis and social media data processing. The keywords listed in the table reveal multiple research hotspots of machine learning in tourism. The “big data" and "deep learning" reflects researchers' focus on big data analysis and deep learning algorithms; "sentiment analysis" and "social media" indicate that sentiment analysis and social media data processing are important directions for research. In addition, the keywords "prediction" (28 times) and "model" (53 times) reveal the application of machine learning in tourism demand prediction and model construction. The high frequency of these keywords indicates that the application of machine learning technology in tourism research is not only limited to the traditional analysis of tourists' behaviors but also covers a variety of aspects such as sentiment analysis and social media data processing.

TABLE V. VISUALIZATION OF "TOURISM" AND "MACHINE LEARNING" (I)

| *Id* | *Keyword* | *Occurrences* | *Total link strength* |
|---|---|---|---|
| 147 | arrivals | 20 | 37 |
| 151 | artificial intelligence | 42 | 95 |
| 238 | behavior | 22 | 52 |
| 260 | big data | 58 | 166 |
| 382 | classification | 40 | 75 |
| 543 | covid-19 | 23 | 52 |
| 668 | deep learning | 47 | 96 |
| 680 | demand | 40 | 80 |
| 688 | destination | 20 | 53 |
| 1208 | hospitality | 55 | 159 |
| 1290 | impact | 48 | 105 |
| 1526 | machine learning | 282 | 433 |

The total link strength reflects the relevance of the keywords. The high link strength between "machine learning" and "tourism" (433 vs. 285) indicates a strong association between the two in the study. In addition, the link strength between "big data" and "deep learning" is also high (166 vs. 96), indicating that these two techniques are often discussed side by side in research. Other keywords such as "sentiment analysis" and "social media" have high link strengths (150 vs. 152), suggesting that sentiment analysis and social media data processing are often discussed side by side in research. These correlation analyses reveal that machine analysis and social media data processing are often explored simultaneously in research [20]. These linkage analyses reveal the multidimensional character of machine learning in tourism research, i.e., researchers not only focus on the traditional analysis of tourists' behaviors but also pay attention to various aspects such as sentiment analysis and social media data processing. The occurrence of keywords such as "natural language processing" (natural language processing, 22 times) and "random forest" (random forest, 23 times) suggests that the natural language processing and the random forest algorithms are gradually increasing in tourism research. Natural language processing techniques can be used to analyze tourists' review data, while random forest algorithms can be used for tourists' behavior prediction. In addition, the occurrence of "COVID- 19" (new crown epidemic, 23 times) suggests that machine learning techniques also play an important role in coping with the impact of new crown epidemics on tourism. The occurrence of these keywords reflects the wide application and innovation of machine learning techniques in tourism research. The appearance of the keywords "satisfaction" (satisfaction, 43 times) and "reviews" (reviews, 25 times) indicates that tourist experience and satisfaction are important directions for machine learning in tourism research. By analyzing tourists' review data and satisfaction, the researcher explores how to improve the quality and attractiveness of the tourism experience. Tourists' satisfaction is identified through sentiment analysis techniques, or tourists' engagement is enhanced through recommendation systems [39]. The appearance of these keywords indicates that the application of machine learning techniques in tourism research not only focuses on technical implementation but also tourists' experience and satisfaction.

TABLE VI. VISUALIZATION OF "TOURISM" AND "MACHINE LEARNING" (II)

| *Id* | *Keyword* | *Occurrences* | *Total link strength* |
|---|---|---|---|
| 1550 | management | 26 | 59 |
| 1647 | model | 53 | 101 |
| 1722 | natural language processing | 22 | 54 |
| 1804 | online reviews | 25 | 73 |
| 1887 | performance | 23 | 63 |
| 1980 | prediction | 28 | 61 |
| 2070 | random forest | 23 | 40 |
| 2174 | reviews | 25 | 78 |
| 2236 | satisfaction | 43 | 109 |
| 2314 | sentiment analysis | 61 | 150 |
| 2401 | social media | 51 | 152 |
| 2645 | tourism | 147 | 285 |

Fig. 4 is the keyword clustering graph generated based on VOSviewer, which shows the correlation between keywords and their clustering characteristics under the topics of "tourism" and "machine learning". Through the clusters of different colors, we can see the research hotspots of machine learning in tourism and its multi-dimensional characteristics [40]. The red clusters in the figure may represent "machine learning technology and algorithm application", including "deep learning", and "artificial intelligence". The red clusters may represent "machine learning techniques and algorithm applications", including keywords such as "deep learning", "artificial intelligence", "natural language processing" and "random forest". These keywords reflect the core application of machine learning technology in tourism research, especially the wide application of deep learning and natural language processing technology in the analysis of tourists' behavior and sentiment analysis. The green clusters may represent "tourism demand and prediction", including "demand", and "prediction". The keywords "demand", "prediction" and "model" indicate that the application of machine learning technology in tourism demand prediction and model construction is gradually increasing, especially in tourism flow prediction and resource scheduling optimization. The blue clusters may represent "tourist experience and satisfaction", including "satisfaction", "reviews" and "sentiment analysis". The keywords "satisfaction", "reviews" and "sentiment analysis" reveal the important role of machine learning in visitor experience optimization and satisfaction enhancement, such as identifying visitor satisfaction through sentiment analysis techniques or enhancing visitor engagement through recommendation systems.

In addition, the keywords in the cluster diagram reflect the innovative application of machine learning techniques in tourism research. The keywords "big data" and "social media" indicate that big data analysis and social media data processing are important directions for research. Analyzing social media data through machine learning techniques can identify tourists' preferences and behavioral patterns and provide decision support for tourism management [37]. The appearance of the keyword "covid-19" (new crown epidemic) indicates that

machine learning techniques also play an important role in coping with the impact of the new crown epidemic on tourism, such as analyzing the impact of the epidemic on tourism demand through predictive models or evaluating tourists' responses to the epidemic through sentiment analysis techniques. The keywords "destination" and "management" suggest that machine learning techniques are increasingly being used in destination management, for example, through predictive models to optimize the allocation of tourism resources, or through sentiment analysis techniques to improve the performance of tourists [41]. The use of machine learning techniques in tourism destination management is increasing, such as optimizing the allocation of tourism resources through predictive modeling, or improving tourist satisfaction through sentiment analysis techniques.

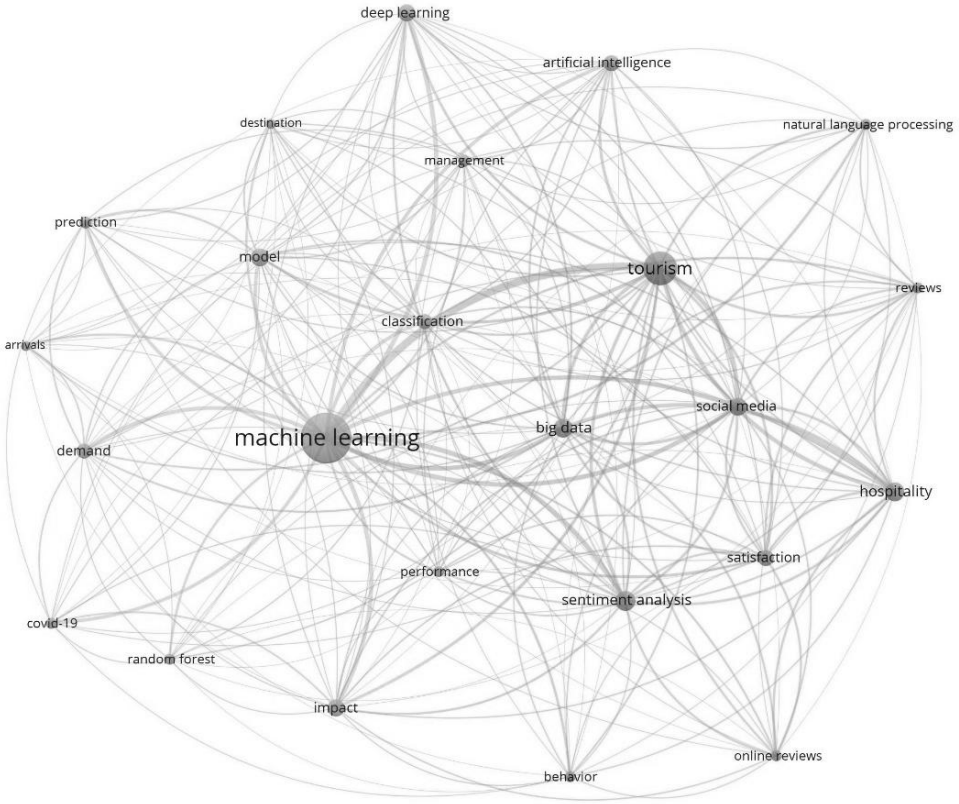


Fig. 4. Basic clustering mapping for machine learning and tourism.

## V. Conclusion

This study reveals the research hotspots, current status of technology applications, and future development direction in the field of cultural heritage tourism experience design by systematically combing the literature trends and the progress of machine learning technology applications in this field. It is found that the research focus of tourism experience design has shifted from traditional conservation and display to visitor experience optimization and technological innovation, especially the introduction of machine learning technology has injected new vitality into related tourism. Through big data analysis, deep learning, natural language processing, and other technologies, machine learning can not only optimize the analysis of tourist behavior and resource management, but also promote the digital protection and innovative display of tourism heritage, and even reconfigure the interaction mode between tourists and culture. In addition, the study shows that the success of tourism cannot be achieved without community participation and cultural identity, and machine learning technologies show great potential in enhancing tourist satisfaction and personalized experience. Overall, this study provides an important theoretical basis and technical support for academic exploration and industry practice of cultural heritage tourism experience design.

There are some limitations in this study. First, the source of the literature data mainly relies on the Web of Science database, which may have the problem of incomplete data coverage, and future research can combine with other databases (e.g. Scopus, CNKI) for a more comprehensive analysis. Second, the application cases of machine learning technology are mostly concentrated in developed countries or regions, with fewer practice cases in developing countries or regions, and future research can further expand the geographical scope and explore the technology's adaptability in different cultural contexts. In addition, the ethical issues of machine learning technology (e.g. data privacy, algorithmic bias) have not yet been fully discussed, so future research needs to find a balance between technological innovation and humanistic values and explore the path of "human-centered" technology adaptation. In the future, with the deepening of multimodal data integration and interdisciplinary cooperation, the application of machine learning technology in tourism will be more extensive and precise, providing more possibilities for the protection, dissemination, and sustainable development of cultural heritage.

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# Netizens as Readers, Producers, and Publishers: Communication Ethics and Challenges in Social Media

Burhanuddin Arafah, Muhammad Hasyim, Herawati Abbas
Faculty of Cultural Sciences, Hasanuddin University, Makassar, Indonesia

***Abstract*—Social media has fundamentally transformed how people communicate and interact, creating a dynamic landscape where today's internet users assume multifaceted roles as readers, producers of text (messages), and publishers of their own content. This evolution empowers individuals to consume information and generate it, offer commentary, and share it widely across platforms. However, this shift brings forth significant ethical considerations that warrant critical examination. This research analyzes the complex issues and challenges surrounding the ethics of social media communication. It emphasizes the urgent need for individuals and society to address these challenges ethically and responsibly in an era where misinformation can spread rapidly, influencing public opinion and societal norms. The research employs a descriptive qualitative method that includes observation of netizen comments on YouTube cases related to corruption and immorality alongside an online questionnaire distributed among social media users. The study draws from two primary data sources: first, netizen comments on various YouTube videos addressing corruption; second, responses from 1,061 participants who completed the online questionnaire. Findings reveal that active participation by netizens enables them to engage in diverse forms of communication—expressing critical views, sharing recommendations for positive change, or even disseminating hate speech in reaction to contentious issues like corruption or moral failings. While some netizens utilize respectful language and promote constructive dialogue through engaging content creation, others contribute to a more toxic environment characterized by negativity. This diversity highlights the potential for positive discourse and the risks associated with unchecked expression on social media platforms. Ultimately, this research underscores that netizens possess substantial opportunities—and responsibilities—to shape public discourse through their actions as readers, producers, and publishers within this evolving digital ecosystem.**

***Keywords*—Netizen; communication ethic; challenge; social media***

## I. INTRODUCTION

Science and technology development has drastically changed how people use advanced media [1]. This development has reached a stage where artificial intelligence (AI) can make life easier [2]. Furthermore, the most prominent development is internet use in daily life. It becomes interesting that internet media content is the most frequently visited [3]. In academic field, the existence of online media is worthwhile for students who tend to use internet at utmost providing the teachers engage in technology-assisted learning [4]. Integrating digital media into the learning process enhances interactive learning experiences as well as developing digital literacy skills [5]. Internet media has become an online public space marked by a significant increase in Internet users, reaching more than 70% of the population of Indonesia in 2023 [6], [7]. Internet users have rapidly expanded as the need to seek knowledge through the Internet has increased [8]. Netizens, a term used to describe active internet users who engage in various online activities, have utilized internet media as an online public space for all activities of internet users, for example, discussions, promotional media, media for delivering the latest information, and any topic considered necessary, urgent, and entertaining is communicated in the online public space.

The online public space that netizens target is social media, a highly interactive medium that facilitates communication and interaction among netizens and social media groups [9], [10]. With a high rate of users, social media netizens are the most active users accessing information [4]. Netizens' role on social media is not limited to being readers of text messages in a media group. The netizens also have the power to create and share news, provide comments, and act as publishers by reporting their comments and sharing existing news with other groups. This active role of netizens in shaping the online public space is a key aspect of our discussion.

An event that often stirs on social media is spreading the news (forward) to social media groups, for example, the news in a WhatsApp (WA) chat about the rejection of an Indian man's proposal by the woman's future in-laws in Makassar, Indonesia. The story of the rejected proposal has also been reported by online media such as Detik.com [11], Liputan6 [12], and Kompas.com [13], which were then spread by netizens to social media groups. Other news is that the incident of abuse went viral, and the video recording was spread on social media, only a matter of an inactive member in the WA Group, who his group friends then beat. The video recording of this abuse circulated in a chain on social media until it was shocking and viral [14]. Other viral news also mentioned the circulation of a video of the destruction of his car using a long-barreled weapon by a police officer going viral on social media [15]. Information from the National Police Security Maintenance Agency stated that since 2019, there have been 26 incidents of social conflict, one of which was caused by the influence of the media. Social conflict occurs because of the high circulation of information spread through social media, and social media users read these messages and share them on other media [16].

Most social media users put their thoughts explicitly by stating them in detail with the intention that the readers will understand directly [17]. The users willingly complain and criticize unpleasant things by writing negative words to express dissatisfaction[18]. Making negative comments in the form of propaganda and hatred and then spreading them on social media is an ethical issue in communicating and a challenge for individuals and society to overcome this ethical problem. Communication delivers informative messages, but people are expected to get misunderstood because of a communication error [19], [20]. The most likely reason is that writing on social media does not require people to write formally by thinking critically to put their arguments [21]. Interpreting and defining messages through comments so that netizens can have the same understanding (meaning) or vice versa with other netizens can cause social conflict [22]. Social conflict occurs on social media only as a matter of interpretation of comments by other netizens. Spreading news (pleasant and unpleasant) to other netizens results from the symbolic interpretation (language and chat culture) of netizens, which shows character and behavior resulting from symbolic interactions. Language as a communication tool is used to convey messages where the writer, text, context, and reader are inseparable to achieve the language's goal [23]. Language must be distinct from its cultural environment, including symbols and signs [24], [25]. It is expected to see internet users use figurative language, such as metaphor or analogy, to give vivid images of the news that the users spread [26].

In addition to having benefits, social media has a wrong side. As the most intelligent creatures on earth, humans can perform appropriate and inappropriate behaviour for specific purposes [27]. The close relationship between humans and their environment, including technological development, has caused unfriendly human behaviour with a careless lifestyle in social life [28], [29]. With the role of netizens as producers and publishers, one of the main problems is the spread of negative comments on news on social media. Negative comments are a form of hate speech by netizens to others. The spread of negative comments can have serious consequences, ranging from damaging the democratic process to endangering public health.

Another problem is cyberbullying, which can cause mental health problems and even suicide [30]. This is where technology changes what used to be cultural-based, where people tended to use the local language proficiently into something less cultural or impolite [31], [32]. The social conflict resulting from this phenomenon is caused by the lack of cultural values in social life [25]. Social media companies are responsible for addressing these issues and designing platforms to prioritize user well-being. If the companies wish to change the character of the young generation, a good influence with a cultural basis is expected to be applied as a guideline to perform good behavior [33], [34]. The attention to local values can increase their awareness of how to behave[35]. Additionally, the role of parents to guide their children of how to behave well is no less important remembering that our young generation is influenced by their closest environment, which is family [36]. Ultimately, it is up to individuals to use social media responsibly and be aware of the risks and ethical considerations involved. Using social media wisely and responsibly can help create a safer and more positive online environment. The more positive the environment is, the more optimist the individuals behave [37].

This study explores ethical issues in communication and their challenges on social media. Ethical issues in communication are related to netizen comments as readers, producers, and publishers of texts on news about corruption, immorality, and bullying. The approach used to answer the research objectives is speech act theory.

This paper is structured first to provide a comprehensive review of the existing literature on communication ethics in social media, highlighting key theories and frameworks relevant to netizen behavior. Following this, the research methodology employed in the study is presented, detailing the data collection processes and analytical approaches used to examine netizen comments. The findings section outlines the key insights gained from the analysis, focusing on ethical challenges faced by netizens as readers, producers, and publishers. Finally, a discussion of the implications of these findings for individuals and society will be provided, along with limitations and contributions for fostering responsible online engagement among users.

## II. Related Works

The intersection of communication ethics and social media has garnered significant attention in recent years, with various studies exploring the roles of netizens as active participants in digital discourse. A growing body of research highlights individuals' reliance on social media platforms for news consumption and the associated challenges in verifying information accuracy. Arafah and Hasyim [6] further explore that most people get their news from social media like Facebook, WhatsApp, and Instagram. About 90% of users rely on these platforms for information, and 81% often search for news there. Popular topics include COVID-19 vaccination and religious intolerance. However, many users still lack the skills to check whether the information is true or false. As a result, false news spreads easily. The study shows that improving digital literacy is important to help people better understand and share accurate information online.

Another critical aspect is the phenomenon of misinformation and its impact on public discourse. Vosoughi et al. [38] conducted a comprehensive analysis demonstrating how false information spreads more rapidly than true information on social media platforms, raising ethical concerns about accountability among users who share such content without verification. This aligns with concerns regarding netizen behavior when disseminating news related to sensitive topics like corruption or immorality.

Research by Friggeri et al[39] further emphasizes the role of social networks in amplifying both positive and negative comments made by users, illustrating how online interactions can lead to polarization within communities. The study underscores that while some netizens contribute constructively to discussions, others may resort to hate speech or negative commentary that exacerbates conflicts.

Additionally, studies have examined cyberbullying within digital spaces—an issue closely tied to communication ethics—highlighting its detrimental effects on mental health among victims [40]. These findings underscore the urgent need for effective strategies to mitigate harmful behaviors online while promoting respectful engagement among users.

Furthermore, existing literature emphasizes the importance of digital literacy education as a means to empower individuals with critical thinking skills necessary for navigating complex online environments [41]. By fostering awareness around responsible use of technology and understanding ethical considerations inherent in communication practices on social media platforms, individuals can better navigate challenges posed by their roles as readers, producers, and publishers.

Overall, this body of work provides valuable insights into understanding netizen behavior within social media contexts while highlighting ongoing challenges related to communication ethics that necessitate further exploration through empirical research.

## III. Research Method

The research used a descriptive qualitative method [42], [43]. Data was collected through a close reading and understanding [44]. The object of the study is netizen comments on cases on social media. The data collection methods used are 1) observation and 2) recording netizen comments on cases on YouTube and distributing questionnaires online to social media users. There are two data sources: the first data is netizen comments on corruption and immoral cases on YouTube, and the second data is the result of filling out a questionnaire that totals 1061 respondents.

The characteristics of the questionnaire data based on gender (Fig. 1) are 786 men (74%) and 275 women (26%). The jobs held by respondents are from various circles, including students, employees, civil servants, entrepreneurs, and others.

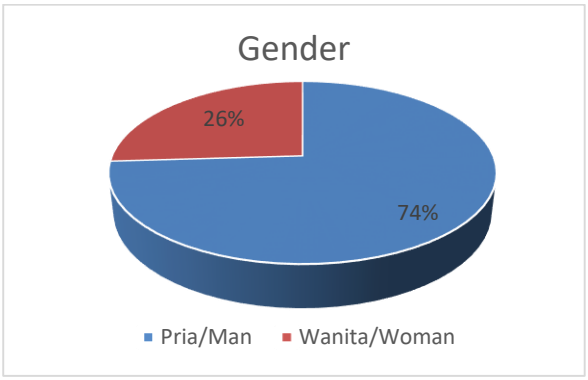


Fig. 1. Number of respondents by gender occupation.

Table I shows that the majority of respondents (61%) were employees, followed by students (21%). Civil servants (10%) and entrepreneurs (7%) made up smaller portions, while only 1% fell into the "other" category. This distribution shows that working individuals make up the bulk of the participants in the study.

Respondents based on education level (Elementary School, Middle School, High School, Diploma, and Master's) were dominated by high school graduates at 72% (see Table II).

TABLE I. Occupation

| Occupation | Presentation | Frequency |
|---|---|---|
| Students | 21% | 221 |
| Employee | 61% | 645 |
| Civil Servant | 10% | 101 |
| Entrepreneur | 7% | 78 |
| Other | 1% | 16 |
| TOTAL | 100% | 1061 |

TABLE II. Last Education

| Last Education | | |
|---|---|---|
| Primary School | 1% | 8 |
| Junior High School | 3% | 34 |
| Senior High School | 72% | 764 |
| Bachelor's Degree | 22% | 237 |
| Master's Degree | 2% | 18 |
| **TOTAL** | **100%** | **1061** |

## IV. Result and Discussion

### A. Speech Act Analysis of Comments on Corruption Cases

#### 1) Netizen comments on corruption cases

Speech: (1) Inikah keadilan? Dimana rakyat dibuat sengsara,negeri dibuat miskin dan melarat oleh sang koruptor.cuma diganjar 10 tahun penjara. semoga muncul hakim yang tegas dan berwibawa bebas sogokan sang koruptor. (Is this justice? Where the people are made miserable, the country is made poor and destitute by the corruptor, only given 10 years in prison. Hopefully there will be a firm and authoritative judge free from bribes by the corruptor)

Context: The @suhardisuhardi1001 account commented on the news of Syahrul Yasin Limpo's verdict on YouTube, which was a meager sentence for a corruption case.

The comment "Is this justice?" in Table III is a form of directive speech in the form of a question. The word's meaning is intended to satirize the results of the judge's decision to be known to people in cyberspace. The sentence "Where the people are made miserable, the country is made poor by the corruptor. Only given ten years in prison. Hopefully, there will be a firm and authoritative judge free from bribes by the corruptor." the utterance is identified as an assertive satirical utterance.

The grammatical analysis of the sentence that the country is made poor means that because of the many corruptors who only get light sentences, the country is not progressing, and society is increasingly impoverished. The word justice is often related to the same punishment and government policies. Hopefully, there will be a firm and authoritative judge, an expressive speech act in which the speaker hopes that later, there will be a

judge who can be fair in punishing corrupt officials and ordinary people. The words firm and authoritative refer to how the judge makes legal decisions for suspects. This utterance is intended to satirize by expressing the speaker's opinion about the punishment of corruptors. Based on the analysis, the utterance in this sentence contains hate speech in the form of sarcasm.

The governments can adopt various roles and procedures. The government should establish clear regulatory frameworks that outline acceptable online behavior, including age verification systems to protect younger users. Collaborating with social media companies to develop robust content moderation policies and conducting regular audits will ensure accountability. Public awareness campaigns focused on digital literacy can educate citizens about responsible online behavior and promote ethical engagement.

Additionally, partnerships with tech companies to create tools for detecting misinformation, along with data-sharing agreements for better monitoring trends while respecting privacy, are essential. Supporting research initiatives on netizen behavior's impact on public discourse will foster innovative solutions to ethical challenges. Developing crisis response protocols for misinformation during critical events ensures timely intervention by authorities, while clear reporting mechanisms empower users to report harmful content easily.

Collectively, these measures enable governments to play a proactive role in promoting safer online environments and empowering citizens through education about responsible engagement within digital spaces.

Speech: (2) Fonis 10th, dikurangi remisi dan kelakuan baik, dikurangi sakit dll. Jadinya paling 1th itupun bonus fasilitas ruangan kelas VVIP, pelayanan hotel bintang 7..... Enak betuuuuuuul..... Serahkan kepada kami saja pak, biar yg kami hukum ga lama, ga bikin susah, ga nambah biaya, tuntas selama lamanya....hehehehe saya siap eksekusinya, cuma pisahkan aja kepala sama batang lehernya, biaya minim cuma biaya peti dan kuburan (10 years in prison, minus remission and good behavior, minus illness, etc. So the most 1 year is a bonus of VVIP class room facilities, 7-star hotel services..... Really nice..... Just leave it to us, sir, so that what we punish will not be long, will not cause trouble, will not add costs, will be finished forever....hehehehe I am ready to execute him, just separate his head from his neck, the minimum cost is only the cost of the coffin and grave.)

Context: The account @shidkonajunrisarsid6581 wrote in the comment's column expressing his desire to punish the corruptors in the YouTube video himself because a 10-year sentence does not have a deterrent effect on corruptors who can even still get special treatment in prison cells.

The comment "serahkan kepada kami saja pak" (leave it to us, Sir) refers to the corruptors, then the word "Kami" (We) refers to the owner of the @shidkonajunrisarsid6581 account who will punish the corruptors himself.

The sentence "biar yg kami hukum ga lama, ga bikin susah, ga nambah biaya, tuntas selama lamanya....hehehehe saya siap eksekusinya, cuma pisahkan aja kepala sama batang lehernya, biaya minim cuma biaya peti dan kuburan (so that our punishment is not long, does not cause trouble, does not add costs, is finished forever....hehehehe, I am ready to execute, just separate the head from the neck, the minimum cost is only the cost of the coffin and grave), which is written in all capital letters indicates the emphasis on each word written. Writing capital letters can be considered as an outburst of emotion such as anger, hatred towards the object being targeted. The utterances that are uttered can contain hate speech giving a warning. The speaker warns the one who has given the punishment to the corruptor to give Syahrul Yasin Limpo to the account @shidkonajunrisarsid6581 to be executed himself.

TABLE III. NETIZEN COMMENTS ON CORRUPTION CASES

| No. | Account | Comment | Forms of Speech Acts |
|---|---|---|---|
| 1 | @suhardisuhardi1001 | *Inikah keadilan? Dimana rakyat dibuat sengsara, negeri dibuat miskin dan melarat oleh sang koruptor, cuma diganjar 10 tahun penjara. Semoga muncul hakim yang tegas dan berwibawa bebas sogokan sang koruptor.*<br>(Is this justice? Where the people are made miserable, the country is made poor and destitute by the corruptor, only given 10 years in prison. Hopefully there will be a firm and authoritative judge free from bribes by the corruptor.) | Assertive, Expressive, and Directive (sarcasm) |
| 2 | @shidkonajunrisarsid6581 | *Fonis 10th, dikurangi remisi dan kelakuan baik, dikurangi sakit dll. Jadinya paling 1th itupun bonus fasilitas ruangan kelas VVIP, pelayanan hotel bintang 7..... ENAK BETUUUUUUUL..... SERAHKAN KEPADA KAMI SAJA PAK, BIAR YG KAMI HUKUM GA LAMA, GA BIKIN SUSAH, GA NAMBAH BIAYA, TUNTAS SELAMA LAMANYA....HEHEHEHE SAYA SIAP EKSEKUSINYA, CUMA PISAHKAN AJA KEPALA SAMA BATANG LEHERNYA, BIAYA MINIM CUMA BIAYA PETI DAN KUBURAN.....*<br>(10 years sentences, minus remission and good behavior, minus illness, etc. So, the most 1 year is a bonus of VVIP classroom facilities, 7-star hotel service.....<br>REALLY GOOD..... JUST LEAVE IT TO US, SIR, SO THAT WE PUNISH WILL NOT TAKE LONG, WILL NOT MAKE IT DIFFICULT, WILL NOT INCREASE COSTS, COMPLETE FOREVER....HEHEHEHE, I'M READY TO EXECUTE IT; JUST SEPARATE THE HEAD FROM THE NECK; THE MINIMAL COST IS JUST THE COST OF THE COFFIN AND GRAVE.....) | Directive and Assertive (giving a feeling of anger and annoyance) |
| 3 | @raffagamers5124 | *Kasus korupsi terburuk dalam sejarah negara ini masa cuman 10 tahun...klo bebas nanti masih bisa cari jabatan sirakus ini...*<br>(The worst corruption case in the history of this country, only 10 years... if he is released later, this greedy person can still find a position...) | Assertive (bullying/swearing) |

Source: https://www.youtube.com/watch?v=bg_w5hii3BQ

The utterance “serahkan kepada kami saja pak, biar yg kami hukum ga bikin susah, ga nambah biaya, tuntas selama lamanya....hehehehe” (leave it to us, Sir, so that what we punish will not make it difficult, will not add costs, will be finished forever....hehehehe) is a directive act in the form of a request where the speaker expresses his desire so that the corruptor can be executed himself later. The utterance "10 years in prison, minus remission and good behaviour, and minus illness. So at most one year and that too with a bonus of VVIP classroom facilities" is an assertive speech act in the form of insinuation where even though the punishment received is light, the corruptors still get special treatment by getting many facilities in the prison cell. The sentence "so that what we punish will not make it difficult" is identified as hate speech, giving a sense of anger and annoyance because the punishment given to the corruptor is very light; it can be reduced, and the speaker asks for the corruptor to be handed over to be executed himself by the account @shidkonajunrisarsid6581.

Speech: (3) Kasus korupsi terburuk dalam sejarah negara ini masa cuman 10 tahun...klo bebas nanti masih bisa cari jabatan sirakus ini (The worst corruption case in the history of this country, only 10 years... if he is released later, he can still seek a position, what a greedy man)

Context: Akun @raffagamers5124 menulis komentar dalam video YouTube yang menampilkan koruptor Syahrul Yasin Limpo. Penutur mengomentari bahwa negara ini sangat buruk dalam menangani kasus korupsi yang mana koruptor tidak mendapatkan hukuman yang setimpal atau bisa bebas dengan cepat (The account @raffagamers5124 wrote a comment on a YouTube video featuring corruptor Syahrul Yasin Limpo. The speaker commented that this country is very bad at handling corruption cases where corruptors do not get appropriate punishment or can be released quickly).

The word “greedy” in the speech is identified as hate speech bullying in the form of curses. The phrase “masih bisa cari jabatan si rakus ini” (can still seek a position, what a greedy man) indicates curses towards someone. Lexically, the word “greedy” in Indonesian means likes to eat a lot without choosing, greedily, gorging, greedy. Grammatically, the sentence “masih bisa cari jabatan si rakus ini” (this greedy person can still find a position) means that the punishment given to the corruptor is too light so that when Syahrul Yasin Limpo is free, he can still find a job. This causes the perpetrators of corruption not to get a deterrent effect.

A pragmatic analysis of the sentence “Kasus korupsi terburuk dalam sejarah negara ini masa cuman ten tahun...klo bebas nanti masih bias cari jabatan si rakus ini..." (The worst corruption case in the history of this country, only ten years... if he is released later, he can still find a position for this greedy person) seen from the context is an assertive illocutionary speech act. The account @raffagamers5124 stated that satirizing the judge's decision to sentence the corruptor to only ten years was too light for a corruptor who had caused much harm to the state and society.

*2) Indecent case against the chairman of the general election commission:* The indecent case against the Chairman of the General Election Commission of Indonesia has sparked controversy and public outcry, raising concerns about integrity within electoral institutions, as seen in Table IV. Allegations of inappropriate conduct undermine the commission's credibility, leading to calls for an investigation and intensifying discussions about ethical standards in overseeing fair elections.

TABLE IV. NETIZEN COMMENTS ON IMMORAL CASES

| No. | Account | Comment | Forms of Speech Acts |
|---|---|---|---|
| 2 | @kutilangaja9157 | *Menurut sy itu bukan kasus asusila krn mau sama mau, tepatnya itu adalah kasus KORUPSI! Mestinya pidana, bukan cm dipecat tp dihukum pidana!!* (In my opinion, it is not a case of immorality because they like each other. To be precise, it is a case of corruption. It should be criminal, not just fired but punished criminally!!) | Assertive (giving a sense of anger and upset) |
| 3 | @WenayBaruaja | *Pecat miskinkan dan penjara kan.... Setuju yuu* (Fire, impoverish, and imprison, right? You agree, right? | Assertive (giving a feeling of anger and annoyance) |
| 7 | @nofelice | *Gak ngerti lg apa itu asusila... sdh terjadi gitu lama tp nyebutnya asusila??? Gk sekalian lapornya di perkaoos aja sekalian gtu... kiamat ini mah* (I don't understand what immorality is anymore... it's been going on for so long but they call it immorality??? Why not just report it as rape... this is the end of the world) | Commissive (giving a feeling of anger and annoyance) |

Source: https://www.youtube.com/watch?v=QMUCNwBgad8

Speech: (2) Menurut sy itu bukan kasus asusila krn mau sama mau, tepatnya itu adalh kasus KORUPSI! Mestinya pidana, bukan cm dipecat tp dihukum pidana!! (In my opinion, it is not a case of immorality because they like each other. To be precise, it is a case of CORRUPTION. It should be criminal, not just fired but punished criminally!!)

*3) Context:* Akun @kutilangaja9157 menulis komentar bahwa penutur meyakini kasus Hasyim bukan kasus asusila melainkan kasus korupsi dan harus ditindaklanjuti agar pelaku mendapatkan hukuman pidana (The @kutilangaja9157 account wrote a comment that the speaker believes that Hasyim's case is not a case of immorality but rather a case of corruption and must be followed up so that the perpetrator receives criminal punishment.)

The phrase “bukan kasus asusila” (not an immoral case) refers to the case that happened, namely the corruption case committed by Hasyim and CAT (Cindra Aditi Tejakinkin). Hermeneutically, the sentence “Menurut sy itu bukan kasus asusila karena mau sama mau” (According to me, it is not an immoral case because they both wanted to) means that the speaker states his belief that the immoral case did not happen because Hasyim and CAT liked each other, so no one was harmed. The pragmatic analysis of the sentence “tepatnya itu adalah kasus KORUPSI!” (precisely, it was a CORRUPTION

case!) Seen from the speaker's comment context, it is an assertive illocutionary speech act. The speaker of the @kutilangaja9157 account concluded that the immoral case was only an excuse because what happened was an indication of corruption committed by Hasyim by giving luxury goods to CAT and allegedly using state money. The comment "Mestinya pidana, bukan cm direct tp dihukum pidana!!" (It should be criminal, not just fired but punished criminally!!) is also an assertive speech act that demands that the perpetrator not only be fired but also arrested because the perpetrator is suspected of embezzling state money by giving it to CAT.

Speech: (3) Pecat miskinkan dan penjara kan.... Setuju yuu (Fire, impoverish, and imprison, right? I agree, right?)

Context: The @WenayBaruaja account commented on wanting Hasyim to be fired, his assets confiscated, and his imprisonment.

The phrase "miskinkan" (impoverish) refers to confiscating assets owned by corruptors from the proceeds of taking state money. The pragmatic analysis of the sentence "Pecat miskinkan dan penjarakan...." (Fire, impoverish and imprison kan ....) seen from the context of the speech is an assertive illocutionary speech act. The speaker of the @WenayBaruaja account demands and urges the authorities to confiscate assets or goods used for personal gain and investigate Hasyim to prove the speaker's allegations and people who suspect a corruption case. The hate speech identified in this speech shows anger and annoyance. "Pecat, miskinkan dan penjarakan...." (Fire, impoverish, and imprison ....) is a comment from the speaker who wants corruptors to receive heavier sentences. If the perpetrators are proven to have committed corruption, the perpetrators will be imprisoned to provide a deterrent effect. Impoverishing and imprisoning corruptors is expected to be the hope of the community for the law to be enforced in Indonesia. There is also hate speech in the form of provocation identified in this speech, namely the expression "setuju yuu" (You agree, right?), which is an invitation for the speaker to agree with his statement regarding the punishment that corruptors must receive.

Speech: (7) Gak ngerti lg apa itu asusila... sdh terjadi gitu lama tp nyebutnya asusila??? Gk sekalian lapornya di perkaoos aja sekalian gtu... kiamat ini mah (I don't understand what immorality is anymore... it's been going on for so long but they call it immorality??? Why not just report it as rape... this is the end of the world)

Context: The @nofelice account wrote a comment indicating that the speaker did not believe what CAT experienced was immoral because they had lived together for a long time. The speaker assumes this is not a case of immorality but leads to corruption.

The phrase "Gk sekalian lapornya di perkaoos aja" (Why not just report it as a rape...) hermeneutically means that CAT reported Hasyim on charges of immorality. Still, the speaker did not believe it because the speaker had known each other for a long time, and their relationship had been going on for a long time. Pragmatic analysis of the sentence "sdh terjadi gitu lama tp nyebutnya asusila??? Gk sekalian lapornya di perkaoos aja sekalian gu..." (it has been going on for so long, but they call it immorality??? Why not just report it as a rape...) seen from the context of utterance is a commissive illocutionary speech act. The speaker rejects the immoral statement reported by CAT. Netizens, including the speaker, criticized the gift of luxury goods from Hasyim to CAT, which was suspected of using public money. The hate speech identified in this speech conveys feelings of anger and annoyance.

### *B. Digital Communication Ethics on Social Media*

The data in Table V shows the need to know how respondents express themselves more freely (broadly) with relaxed language to joke, greet, mock, tease, and express pleasure or displeasure on social media, which is obtained with a scale of strongly disagree 45.81% of respondents answered and a scale of disagree 24.79%. The agreed scale is 16.78%, while the scale of strongly agree is 12.63%.

TABLE V. SOCIAL MEDIA AS A MEDIUM FOR FREEDOM OF LANGUAGE USE FOR EXPRESSION

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very not agree | 486 | 45.8 | 45.8 | 45.8 |
| | Not Agree | 263 | 24.8 | 24.8 | 70.6 |
| | Agree | 178 | 16.8 | 16.8 | 87.4 |
| | Very agree | 134 | 12.6 | 12.6 | 100.0 |
| | Total | 1061 | 100.0 | 100.0 | |

The scale of strongly disagree and disagree is the highest, where many respondents do not want to express their feelings freely on social media. The information needed is one of the functions of the mass media to inform by requiring respondents' answers to know what needs and does not need to be done in expressing self-expression on social media. Especially on social media, you must be more careful in expressing your feelings because it can be a digital footprint.

TABLE VI. CAREFULLY CHOOSE WORDS (VOCABULARY) THAT I WRITE SO AS NOT TO GIVE RISE TO NEGATIVE PERCEPTIONS OF THE PERSON I AM TALKING TO

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very not agree | 12 | 1.1 | 1.1 | 1.1 |
| | Not Agree | 58 | 5.5 | 5.5 | 6.6 |
| | Agree | 410 | 38.6 | 38.6 | 45.2 |
| | Very agree | 581 | 54.8 | 54.8 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

Based on the data above (Table VI), there is a need for responses to determine how respondents communicate on social media, and respondent should be cautious in choosing words (vocabulary) not to cause negative perceptions to the interlocutor. Most respondents answered with a scale of strongly agree, 54.76%, and the agree scale has a percentage of 38.64%. For the disagree scale, 5.47%, while the strongly disagree scale has the lowest rate of 1.13%. Most respondents strongly agree that when writing something on social media, the respondent should be more careful to avoid misunderstandings that could lead in a negative direction.

TABLE VII. PROVIDING COMMENTS ON SOCIAL MEDIA WITHOUT REGARD TO STATUS, AGE, RANK (POSITION) OF A PERSON AS A PERPETRATOR IN A CASE (CORRUPTION, SEXUAL HARASSMENT, CYBERBULLYING, AND DEFAMATION)

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very not agree | 496 | 46.7 | 46.7 | 46.7 |
| | Not Agree | 313 | 29.5 | 29.5 | 76.2 |
| | Agree | 119 | 11.2 | 11.2 | 87.5 |
| | Very agree | 133 | 12.5 | 12.5 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

From the data above (Table VII), it can be seen that the response to find out how respondents communicate by giving comments on social media, without considering the status, age, rank (position) of a person as a perpetrator in a case (corruption, sexual harassment, cyberbullying, and defamation) received responses from respondents who answered the scale strongly disagree with a percentage of 46.75% and the disagree scale has a percentage of 29.50%. The agree scale has the lowest percentage, 11.22%, while the strongly agree scale is 12.54%. The majority of respondents chose the response (strongly disagree) when commenting because they still care about status, age, and other factors on social media. The lowest scale, namely (agree), means not caring about age and rank when writing comments on social media.

Comments written on social media can have positive and negative effects depending on the reader's point of view. Everyone has the right and is free to comment, even though it can sometimes offend other people's feelings. Writing comments is also a form of expressing emotions that you want to convey.

Many news topics can be accessed daily on social media. Respondents can choose several from the five topics provided as answers to determine which news topics are most frequently accessed. The results of the data obtained can be seen in Table VIII.

TABLE VIII. NEWS TOPICS (INFORMATION) THAT ARE MOST FREQUENTLY ACCESSED (READ) EVERY DAY ON SOCIAL MEDIA

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Cases (corruption, sexual harassment, cyberbullying and defamation) | 254 | 23.9 | 23.9 | 23.9 |
| | Entertainment | 357 | 33.6 | 33.6 | 57.6 |
| | Lifestyle | 137 | 12.9 | 12.9 | 70.5 |
| | Sport | 223 | 21.0 | 21.0 | 91.5 |
| | Politic | 90 | 8.5 | 8.5 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

Based on the data in the Table VIII, entertainment news topics are most frequently accessed and in demand on respondents' social media with a percentage of 33.6%. Meanwhile, information topics in the form of cases (corruption, sexual harassment, cyberbullying, and defamation) are in second place with a percentage of 23.9%. Therefore, it is undeniable that many respondents prefer information containing elements of entertainment to entertain them in between daily activities. The information topic on social media in third place is sports, with a percentage of 21.0%, and in fourth place is the lifestyle topic, with an access percentage of 12.9%. The fifth least accessed information topic is politics, with a percentage of 8.5%. Based on the number of respondents' answers, entertainment news topics are more in demand than politics.

TABLE IX. NEWS READING RELATED TO CORRUPTION CASES, SEXUAL HARASSMENT, CYBERBULLYING, DISCRIMINATION, DEFAMATION, MISOGYNY, TROLLING (DELIBERATE ACTIONS TO PROVOKE ANGER), AND MICRO-AGGRESSION

| | | Frequency | Per cent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Seldom | 4 | .4 | .4 | .4 |
| | Average | 49 | 4.6 | 4.6 | 5.0 |
| | Often | 261 | 24.6 | 24.6 | 29.6 |
| | Very often | 506 | 47.7 | 47.7 | 77.3 |
| | Seldom | 241 | 22.7 | 22.7 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

Based on the data in Table IX, respondents gave responses to reading news related to corruption cases, sexual harassment, cyberbullying, discrimination, defamation, misogyny, trolling (deliberate actions to provoke anger), and micro-aggression, where the variations were varied. Most respondents answered often, with a percentage of 47.69% and an average scale percentage of 24.60%. The widespread scale has a percentage of 22.71%, while the rare scale is only 4.6%. Meanwhile, respondents who answered very rarely have a percentage of 0.38%. The majority of respondents often read news with topics related to corruption cases, sexual harassment, cyberbullying, discrimination, defamation, misogyny, trolling, and micro-aggression.

Technological advances make it easier for people to share things they get, including sharing several types of news on social media. The kind of news related to the case is widely shared as a form of caution so as not to experience similar instances. To find out the type of news related to the case, respondents can choose several types of news provided as answers, as stated in Table X.

Table X shows that the type of cyberbullying news is in first place most often shared by respondents on social media, with a percentage of 29.78%. For the kind of news about sexual harassment cases, it is in second place with a percentage of 20.17%. This shows that respondents are aware that cases such as the data above must be prevented by sharing them on social media as a form of lesson so that similar cases do not happen again in everyday life. Both cases often occur in cyberspace and the natural world so that they can be the most shared type of news.

TABLE X. TYPES OF CASE-RELATED NEWS SHARED ON SOCIAL MEDIA

| | | Frequency | Per cent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | corruption case | 78 | 7.4 | 7.4 | 7.4 |
| | sexual harassment | 214 | 20.2 | 20.2 | 27.5 |
| | Cyberbullying | 316 | 29.8 | 29.8 | 57.3 |
| | defamation | 204 | 19.2 | 19.2 | 76.5 |
| | Misogynyi | 128 | 12.1 | 12.1 | 88.6 |
| | Trolling | 81 | 7.6 | 7.6 | 96.2 |
| | Micro-Aggression | 33 | 3.1 | 3.1 | 99.3 |
| | Genocide | 1 | .1 | .1 | 99.4 |
| | Indictment information | 1 | .1 | .1 | 99.5 |
| | Economy and stocks | 5 | .5 | .5 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

The type of news on social media that is in third place is defamation, with a percentage of 19.23%, and for fourth place is the type of misogyny news, which has a percentage of being shared 12.06%. The fifth-place respondents answered that the kind of news shared was trolling, with a percentage of 7.63%. The sixth place is the type of corruption case news, with a percentage of 7.35%. The seventh place is the type of micro-aggression news, with a percentage of 3.11%. The eighth place is the type of economic and stock news, with a percentage of 0.47%. Meanwhile, the kinds of news and preaching information about genocide have the same percentage and are the lowest, namely, 0.09%.

TABLE XI. NEGATIVE COMMENTS ON NEWS CONTENT RELATED TO CASES (CORRUPTION, SEXUAL HARASSMENT, CYBERBULLYING, DEFAMATION, MISOGYNY, TROLLING, MICRO-AGGRESSION (ACTS OF HARASSMENT AGAINST MARGINALIZED GROUPS)

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very seldom | 26 | 2.5 | 2.5 | 2.5 |
| | Seldom | 51 | 4.8 | 4.8 | 7.3 |
| | Average | 214 | 20.2 | 20.2 | 27.4 |
| | Often | 496 | 46.7 | 46.7 | 74.2 |
| | Very often | 274 | 25.8 | 25.8 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

Based on the data obtained from Table XI, it shows that respondents gave responses related to negative comments on news content related to cases (corruption, sexual harassment, cyberbullying, defamation, misogyny, trolling, and micro-aggression (harassment of marginalized groups), which are diverse. Most respondents answered often with a percentage of 46.75%, and the widespread scale had a percentage of 25.82%. The average scale had a percentage of 20.17%, while the rare scale reached a percentage of 4.81%. Meanwhile, respondents who answered very rarely had a percentage of 2.45%. This proves that many respondents gave frequent responses that referred to negative comments on news content related to cases that occurred.

TABLE XII. SHARING NEWS OF CORRUPTION CASES, SEXUAL HARASSMENT, CYBERBULLYING, DEFAMATION, MISOGYNY, TROLLING, MICRO-AGGRESSION (HARASSMENT OF MARGINALIZED GROUPS) ON SOCIAL MEDIA

| | | Frequency | Per cent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Seldom | 20 | 1.9 | 1.9 | 1.9 |
| | Average | 66 | 6.2 | 6.2 | 8.1 |
| | Often | 239 | 22.5 | 22.5 | 30.6 |
| | Very often | 471 | 44.4 | 44.4 | 75.0 |
| | Seldom | 265 | 25.0 | 25.0 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

The data obtained in Table XII shows that respondents gave responses related to sharing news of corruption cases, sexual harassment, cyberbullying, defamation, misogyny, trolling, and micro-aggression (harassment of marginalized groups) on social media, which were diverse. The most choices and responses of respondents were on the frequent scale, with a percentage of 44.39%, and the widespread scale of sharing news had a percentage of 24.98%. The responses given on the average scale were 22.53%, compared to the rare scale, with a percentage of 6.22%. The fewest respondents who chose the very rare scale had a percentage of 1.89%. The majority of respondents chose the frequent scale, which proves that respondents share more news on social media related to cases that occur.

There are several types of information that respondents comment on related to cases on social media. Respondents can choose several types of news from the ten choices given (Table XIII) to find out the kind of news that is commented on.

TABLE XIII. TYPES OF INFORMATION (NEWS) COMMENTED ON BY NETIZENS

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Corruption Case | 91 | 8.6 | 8.6 | 8.6 |
| | Sexual Harassment | 165 | 15.6 | 15.6 | 24.1 |
| | Case Cyberbullying | 200 | 18.9 | 18.9 | 43.0 |
| | Defamation of Good Name | 180 | 17.0 | 17.0 | 59.9 |
| | Misogyny | 162 | 15.3 | 15.3 | 75.2 |
| | Trolling | 167 | 15.7 | 15.7 | 91.0 |
| | Micro-Aggression | 85 | 8.0 | 8.0 | 99.0 |
| | Economy | 1 | .1 | .1 | 99.1 |
| | Sports | 3 | .3 | .3 | 99.3 |
| | Rarely share information | 7 | .7 | .7 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

Based on the data in the Table XIII, it can be seen that the type of information most often commented on by respondents is in the case of cyberbullying, which is in first place, with a percentage of 18.85%. The type of information netizens choose in second place is defamation cases, with a percentage of

16.97%. This shows that netizens often comment on cases of sexual harassment and defamation. The type of information on social media chosen is in third place, namely trolling, with a percentage of 15.74%, and in fourth place is the type of information on sexual harassment, with a percentage of 15.55%. The fifth place is misogyny, with a percentage of 15.27%. The sixth place is corruption cases, with a percentage of 8.58%.

TABLE XIV. NETIZENS FIRST CROSS-CHECK THE TRUTH OF NEWS CONTAINING HATE SPEECH BEFORE SPREADING THE NEWS

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very not agree | 18 | 1.7 | 1.7 | 1.7 |
| | Not Agree | 50 | 4.7 | 4.7 | 6.4 |
| | Agree | 468 | 44.1 | 44.1 | 50.5 |
| | Very agree | 525 | 49.5 | 49.5 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

The data obtained in Table XIV shows that the majority of respondents who answered the scale strongly agree, with a percentage of 49.48% checking the truth of the news before the news is shared on social media and as many as 44.11% who stated they agree. This proves that respondents do research first and look for facts before spreading news that refers to hate speech so that the spread of news does not cause misunderstandings in readers and negative comments can be avoided.

TABLE XV. DISSEMINATING INFORMATION CONTAINING SARA (ETHNICITY, RELIGION, AND RACE) ELEMENTS AND PORNOGRAPHY ON SOCIAL NETWORKS

| | | Frequency | Per cent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Very not agree | 564 | 53.2 | 53.2 | 53.2 |
| | Not Agree | 301 | 28.4 | 28.4 | 81.5 |
| | Agree | 109 | 10.3 | 10.3 | 91.8 |
| | Very agree | 87 | 8.2 | 8.2 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

Based on the data in Table XV that has been obtained, it shows that the responses given by respondents regarding the dissemination of information containing SARA (Ethnicity, Religion, and Race) elements and pornography on social networks stated that they disagree 53.16%. The disagree scale had a percentage of 28.37%. By referring to the percentage above, the agreed response was 10.27%, while the fewest respondents' answers were on the strongly agreed scale, reaching 8.20%. This shows that the majority of netizens do not agree to disseminate news containing SARA and pornography that can cause controversy or conflict in society.

The data obtained in Table XVI shows that netizens mainly chose answers on the scale of strongly disagreeing to upload photos of violence with a percentage of 50.71%, and the second largest scale of disagreeing with a percentage of 32.89%. Then, the percentage of strongly agreeing responses was 9.90%, while the fewest respondents responded on the agreed scale with a percentage of 6.50%. Therefore, it is inevitable that many respondents prefer not to upload photos of violence in any form.

TABLE XVI. UPLOADING PHOTOS OF VIOLENCE, SUCH AS PHOTOS OF VICTIMS OF VIOLENCE, PHOTOS OF TRAFFIC ACCIDENTS, OR PHOTOS OF VIOLENCE IN OTHER FORMS ON SOCIAL MEDIA

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very not agree | 538 | 50.7 | 50.7 | 50.7 |
| | Not Agree | 349 | 32.9 | 32.9 | 83.6 |
| | Agree | 69 | 6.5 | 6.5 | 90.1 |
| | Very agree | 105 | 9.9 | 9.9 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

TABLE XVII. REASONS FOR SHARING INFORMATION (NEWS) RELATED TO CORRUPTION CASES, SEXUAL HARASSMENT, CYBERBULLYING, MISOGYNY, TROLLING, MICRO-AGGRESSION (HARASSMENT OF MARGINALIZED GROUPS) ON SOCIAL MEDIA

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | As a form of hate speech | 80 | 7.5 | 7.5 | 7.5 |
| | So that other people know about the various cases that are currently happening. | 515 | 48.5 | 48.5 | 56.1 |
| | As a critical attitude toward various cases that occur | 460 | 43.4 | 43.4 | 99.4 |
| | It is a lesson always to be alert and careful. | 6 | .6 | .6 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

According to the data obtained in Table XVII, it can be seen that the respondents gave the most reasons for sharing information related to news cases so that other people know various cases that are currently actual as the reason in first place with a percentage of 48.54%. The second most common reason was a critical attitude towards various cases that occurred, with a percentage of 43.36%. This shows that respondents often choose the reason when sharing information so that others know and share the latest cases on social media.

The reason for sharing information on social media that was chosen was in third place, namely as a form of hate speech, with a percentage of 7.54%. For fourth place, the reason that respondents slightly chose was a lesson to be vigilant and careful, as much as 0.57%.

There are several reasons for giving news comments about cases on social media. This is to find out the reasons for the comments provided; respondents chose from 3 reasons that have been given. The results of the data percentage can be seen in TableXVIII.

Based on the data obtained in Table XVIII, netizens (66.3%) provide comments related to news cases such as corruption, sexual harassment, and others to teach the

perpetrator. The second most common reason for providing advice is with a percentage of 29.31%. This shows that respondents, when providing comments related to news cases, often choose the reason as a lesson, a deterrent effect that social law exists, providing harsh criticism for the perpetrators of the case. The reason for giving comments on news cases that were least chosen by netizens was the form of hate speech, as much as 4.43%.

TABLE XVIII. REASONS FOR COMMENTING ON NEWS CASES OF CORRUPTION, SEXUAL HARASSMENT, CYBERBULLYING, MISOGYNY, TROLLING, AND MICRO-AGGRESSION (HARASSMENT OF MARGINALIZED GROUPS) ON SOCIAL MEDIA

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Give a lesson to the perpetrator | 703 | 66.3 | 66.3 | 66.3 |
| | Giving Advice | 311 | 29.3 | 29.3 | 95.6 |
| | Forms of hate speech | 47 | 4.4 | 4.4 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

TABLE XIX. REASONS FOR SHARING INFORMATION (NEWS) RELATED TO CORRUPTION CASES, SEXUAL HARASSMENT, CYBERBULLYING, MISOGYNY, TROLLING, MICRO-AGGRESSION (HARASSMENT OF MARGINALIZED GROUPS) ON SOCIAL MEDIA AS A FORM OF HATE SPEECH

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very not agree | 39 | 3.7 | 3.7 | 3.7 |
| | Not Agree | 91 | 8.6 | 8.6 | 12.3 |
| | Agree | 444 | 41.8 | 41.8 | 54.1 |
| | Very agree | 487 | 45.9 | 45.9 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

The data obtained in Table XIX shows that the scale of responses chosen by netizens regarding sharing news information related to corruption cases, sexual harassment, cyberbullying, misogyny, trolling, and micro-aggression (harassment of marginalized groups) on social media as a form of hate speech is diverse. Most netizens chose the scale of strongly agreeing to share information with a percentage of 45.90%, and the second highest on the agreed scale had a percentage of 41.85%. Based on the data obtained, it is known that many netizens chose to strongly agree to share news information about cases of sexual harassment, corruption, and so on social media.

TABLE XX. MAKING COMMENTS ON NEWS RELATED TO CORRUPTION CASES, SEXUAL HARASSMENT, CYBERBULLYING, MISOGYNY, TROLLING, AND MICRO-AGGRESSION (HARASSMENT OF MARGINALIZED GROUPS) ON SOCIAL MEDIA AS A FORM OF HATE SPEECH

| | | Frequency | Per cent | Valid Percent | Cumulative Per cent |
|---|---|---|---|---|---|
| Valid | Very not agree | 33 | 3.1 | 3.1 | 3.1 |
| | Not Agree | 90 | 8.5 | 8.5 | 11.6 |
| | Agree | 461 | 43.4 | 43.4 | 55.0 |
| | Very agree | 477 | 45.0 | 45.0 | 100.0 |
| | **Total** | **1061** | **100.0** | **100.0** | |

The data obtained in Table XX shows that the response scale chosen when respondents made comments on news related to corruption cases, sexual harassment, cyberbullying, misogyny, trolling, and micro-aggression (harassment of marginalized groups) on social media as a form of hate speech is very diverse. Most respondents chose the answer on the strongly agree scale to make comments related to the above case as a form of hate speech, with a percentage of 44.96%, and the agree scale had a percentage of 43.45%. Furthermore, the percentage of disagreeing reached 8.48%, while the fewest respondents responded on the strongly disagree scale with a percentage of 3.11%. This shows that many respondents agreed and strongly agreed to comment on various cases as a form of hate speech. The comments made were intended to criticize the instances that occurred.

## V. LIMITATIONS AND CONTRIBUTIONS

While this research offers valuable insights, it also has several potential limitations. Several strategies can enhance the robustness of the research to control the limitations or disadvantages. Expanding data sources by including multiple social media platforms and various content formats will provide a broader understanding of user behaviors. Improving questionnaire design through mixed methods and pilot testing can yield more reliable data. Conducting contextual analyses across different regions will help capture cultural influences on communication practices, while longitudinal studies can track changes over time. Utilizing advanced analytical techniques like natural language processing for sentiment analysis will offer objective insights into user interactions. Increasing sample sizes will improve statistical power, and developing clear ethical guidelines for analyzing user-generated content is essential to maintain integrity in research. Collectively, these strategies aim to mitigate limitations while providing deeper insights into netizens' roles in social media communication ethics, benefiting both academic discourse and practical applications for healthier online environments.

This research makes several important contributions to communication studies and social media ethics. It categorizes netizens into three roles—readers, producers, and publishers—clarifying how they interact with content on social media. By examining the ethical challenges of user-generated content, the study enhances our understanding of how netizens deal with moral dilemmas online and highlights the need for specific ethical guidelines. Using a mix of observations from YouTube comments and data from questionnaires provides real evidence about user behavior regarding sensitive topics like corruption. The findings show a range of communication styles among netizens, from constructive dialogue to hate speech, emphasizing how individual actions can shape public discussions on important issues. Additionally, the research offers practical suggestions for encouraging ethical engagement while addressing harmful behaviors like misinformation spread. Finally, it identifies gaps in current knowledge about communication ethics in social media settings, setting the stage for future studies on similar topics across different platforms or demographics.

These enhancements will contribute not only to academic discourse but also offer practical implications for policymakers,

educators, and platform developers seeking healthier online environments.

## VI. CONCLUSION

Based on the results of the discussion, it can be concluded that netizens have a role on social media that is not only as readers or connoisseurs of text (readers), but also as producers who create content, provide comments, and then share it as publishers on social media, making netizens increasingly accessible to provide various comments on various news content that is accessed. The ethics of communication by netizens in giving comments on numerous cases of law violations (corruption and immorality) show hate speech and critical attitudes and provide advice. However, on the other hand, netizens freely use polite language and have an attitude toward pleasant and entertaining news content. Netizens with a role on social media as readers, producers, and publishers have great opportunities to show critical attitudes as a form of hate speech for news related to cases of violations of the law. Comments conveyed in the media contain hate speech to teach the accused a lesson.

Future work should focus on developing educational programs that enhance digital literacy and critical thinking skills among users, enabling them to navigate online spaces responsibly. Additionally, further research could explore the effectiveness of regulatory frameworks aimed at promoting ethical behavior in digital communication while fostering a culture of respectful discourse within social media platforms.

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# Meter-YOLOv8n: A Lightweight and Efficient Algorithm for Word-Wheel Water Meter Reading Recognition

Shichao Qiao, Yuying Yuan*, Ruijie Qi
School of Computer Science and Technology, Shandong University of Technology, Zibo 255000, Shandong, China

***Abstract*—To address the issues of low efficiency and large parameters in the current word-wheel water meter reading recognition algorithms, this paper proposes a Meter-YOLOv8n algorithm based on YOLOv8n. Firstly, the C2f component of YOLOv8n is improved by introducing an enhanced inverted residual mobile block (iRMB). It enables the model to efficiently capture global features and fully extract the key information of the water meter characters. Secondly, the Slim-Neck feature fusion structure is employed in the neck network. By replacing the original convolutional kernels with GSConv, the model's ability to express the features of small object characters is enhanced, and the number of parameters in the model is reduced. Finally, Inner-EIoU is used to optimize the bounding box loss function. This simplifies the calculation process of the loss function and improves the model's ability to locate dense bounding boxes. The experimental results show that, compared with the original model, the precision, recall, mAP@0.5, and mAP@0.5:0.95 of the improved model have increased by 1.7%, 1.2%, 3.4%, and 3.3% respectively. Meanwhile, the parameters, FLOPs, and model size have decreased by 0.56M, 2.6G, and 0.7MB respectively. The improved model can better balance the relationship between detection performance and computational complexity. It is suitable for the task of recognizing word-wheel water meter readings and has practical application value.**

***Keywords*—Word-wheel water meter; YOLOv8n; global features; slim-neck; loss function**

## I. Introduction

The word-wheel water meter is a common flow measurement instrument widely used in tap water metering, playing a crucial role in helping water utility companies monitor users' water consumption. Due to its simple structure, low cost, and strong anti-interference capability, it is widely used in residential communities and industrial workshops. Traditionally, meter reading is performed manually by staff who visually observe the meter readings and record them by hand. This method is labor-intensive and highly repetitive, consuming significant human and material resources [1], [2]. Additionally, it is susceptible to environmental factors and psychological variations of the staff, leading to errors such as misreadings and omissions. In recent years, object detection algorithms have continuously advanced, especially deep learning-based methods, which have significantly improved accuracy. The use of computer vision technology for fast and accurate reading of word-wheel water meters has become a research hotspot [3].

The methods for recognizing the readings of word-wheel water meters can be divided into two types. One is the optical character recognition (OCR) method. This method first locates the reading area of the water meter, then segments the reading area using image segmentation technology, and finally employs a convolutional neural network to recognize the readings in the segmented area. However, this method has high requirements for image quality and a slow processing speed, making it difficult to meet the reading recognition needs of character wheel water meters in complex scenarios. Another method is to directly perform character detection on the water meter image to read the water meter reading. It omits the intermediate positioning and segmentation steps, making the overall recognition process more concise and efficient. When dealing with a large number of water meter images, direct detection can save more time and computational resources and improve the reading efficiency. Considering the two methods comprehensively, in order to enable the model to complete rapid detection in an environment with limited resources, this paper uses an object detection algorithm to directly recognize the readings of the word-wheel water meters [4].

Object detection algorithms can be categorized into single-stage and two-stage algorithms. Common two-stage algorithms include R-CNN, Fast R-CNN [5], and Faster R-CNN [6]. In two-stage algorithms, a large number of candidate boxes are first generated, followed by object classification and bounding box regression. Since classification and regression need to be performed on numerous candidate regions, the training and inference speed of these algorithms is relatively slow. In practical applications, especially in scenarios requiring real-time detection, this slower detection speed can become a limiting factor.

Single-stage detection algorithms include SSD [7] and the YOLO series [8]. These algorithms perform dense predictions on the input image through a single network, achieving both object detection and localization in one step. Compared to two-stage algorithms, single-stage algorithms require lower computational costs and offer better real-time performance. The YOLO algorithm features an integrated design, enabling it to process images at dozens of frames per second or even higher speeds. This allows for fast localization of water meters and reading recognition, making it particularly suitable for applications with high-speed processing requirements.

In order to achieve accurate and rapid reading of the readings of word-wheel water meters, this paper proposes a

lightweight word-wheel water meter reading recognition algorithm based on YOLOv8n. The main contributions of this paper are as follows:

- Based on the publicly available water meter dataset, a word-wheel water meter dataset in real-world scenarios has been constructed. It includes complete characters and transitional characters, totaling twenty categories. This dataset takes into account various unfavorable factors in the real environment, such as light and noise, providing a data foundation for future research.
- To address the issues of low accuracy and a large number of parameters in the reading recognition of word-wheel water meters, this paper proposes the Meter-YOLOv8n algorithm for word-wheel water meter reading recognition. The detection accuracy and efficiency are improved through the use of C2f-iRMBS, Slim-Neck, and Inner-EIoU.
- Comprehensive experiments have been carried out on the word-wheel water meter dataset, and a visual analysis of the test results has been conducted. It proves the detection performance and generalization ability of the improved algorithm, which is more suitable for the task of reading recognition of word-wheel water meters.

This paper is structured as follows: Section II introduces the related work in the field of word-wheel water meter reading. Section III describes the improved algorithm for reading of word-wheel water meters. Section IV introduces the dataset of word-wheel water meters, the evaluation metrics, and the experimental environment. Section V describes the experimental results and visual analysis. Section VI analyzes the deficiencies of the existing work and the directions for future exploration.

## II. Related Work

### A. YOLOv8 Algorithm

As one of the most renowned algorithms in the YOLO series, YOLOv8 is particularly suitable for application scenarios that require fast real-time object detection, such as autonomous driving [9], video surveillance [10], and drone monitoring [11]. YOLOv8 inherits the structural concept of YOLOv5 [12] and is mainly composed of three parts: the backbone network, the neck network, and the head network.

YOLOv8 preprocesses images using mosaic augmentation, adaptive anchor box calculation, and adaptive grayscale padding. It employs an anchor-free approach to directly predict object centers, thereby improving the speed of Non-Maximum Suppression (NMS) [13]. The backbone is responsible for extracting image features and primarily consists of modules such as Conv, C2f, and SPPF. The neck section integrates and transmits features using a Path Aggregation Network (PAN) structure [14]. The head is responsible for object detection and classification tasks, including a detection head and a classification head. Loss computation is divided into two parts: classification loss and regression loss. The classification loss is trained using Binary Cross-Entropy Loss (BCE Loss), while the regression loss combines Distribution Focal Loss (DF Loss) and CIoU Loss.

YOLOv8 is divided into five different sizes, namely n, s, m, l, and x, according to the depth and width of the network. Taking into comprehensive consideration the size and complexity of the algorithm, this paper selects YOLOv8n as the baseline algorithm for improvement.

### B. Reading Recognition of Word-Wheel Water Meters

To improve the reading recognition accuracy of word-wheel water meters and enhance the representation of transitional characters, Cai et al. [15], proposed an efficient automatic meter localization and recognition method. First, they performed a coarse-to-fine detection of the entire meter to locate the reading region. Then, they used a projection-based method to segment the reading area, and finally, a BP neural network was employed to recognize the segmented meter region. Jawas et al. [16], localized the meter using contour information, segmented the reading region, and then applied OCR technology to recognize the meter characters. Chen et al. [17], used an improved U-Net network to locate the dial's reading region in large-scale water meter images. They then segmented individual characters based on the structural features of the dial and finally performed reading recognition using an improved VGG16 network. Men et al. [18], proposed a water meter reading recognition region segmentation method based on an improved U~2-Net. They designed a modified Double-RSU module based on the RSU module, which increases the depth and complexity of the network, thereby enhancing the model's generalization ability and robustness.

To improve recognition efficiency and achieve rapid acquisition of water consumption data, Li et al. [19], proposed a novel lightweight concatenated convolutional network. This network replaces a certain number of standard 3×3 convolution operations with 1×1 convolutions, resulting in a more efficient and lightweight network with better overall performance. Zou et al. [20], utilized a geometric method to perform rotational correction on water meter images and then employed the WDPDet network to identify the reading region of the water meter. This network is capable of handling complex and variable scenes. Zhang et al. [21], applied homography transformation to geometrically correct the deformed reading region. In the transformation stage, new recognition markers and probability vectors were added between each digit to address the issue of digit rotation. Li et al. [22], adopted an improved YOLOv4 object detection algorithm for reading recognition, expanding the receptive field and reducing the loss of original information by introducing a focus structure. Additionally, they enhanced the network's ability to fuse multi-scale features and improved the representation of transitional characters by constructing cross-stage partial connection modules. Wang et al. [23], proposed the GMS-YOLO algorithm for water meter reading recognition, replacing standard convolutions in the C2f module with Grouped Multi-Scale Convolution (GMSC) to enable the model to acquire receptive fields at different scales, thereby enhancing its feature extraction capability. Moreover, they integrated the Large Separable Kernel Attention (LSKA) mechanism into the SPPF module to improve the perception of small-scale features. Finally, the SIoU bounding box loss function was used instead of CIoU, strengthening the model's object localization ability and accelerating convergence speed.

Although the above-mentioned methods have made significant progress in the research of word-wheel water meter reading recognition, they still face the following challenges.

Due to environmental factors and changes in shooting angles, the proportion of effective characters in water meter images is relatively small, and image distortion may occur. This leads to a decrease in recognition accuracy, and sometimes false detections and missed detections may also occur. In order to improve the detection ability of small object characters and distorted characters, we have integrated shift-wise conv based on the inverted residual mobile block (iRMB) [24] and designed a lightweight and efficient C2f-iRMBS module. It can extract the feature information of water meter characters more efficiently.

Deep learning algorithms rely on stacked multi-layer convolutional networks, which have complex structures and require a large amount of computational resources. To reduce the size of the model, we have introduced the Slim-Neck [25] structure into the neck network. The GSConv module and the VoVGSCSP module can simplify the network structure, reduce the computational complexity of the network, and improve the reading efficiency of word-wheel water meters.

In order to solve the problem of overlapping detection boxes of water meter characters, accelerate the training efficiency of the model and improve the convergence speed of the model, the Inner-EIoU loss function is used to replace the complete intersection over union loss (CIoU loss). This enhances the model's ability to locate dense characters.

## III. Proposed Algorithm

### A. Meter-YOLOv8n

Aiming at the problems of low accuracy, false detections, and missed detections that occur in the practical application of deep learning algorithms, this paper proposes a detection algorithm named Meter-YOLOv8n, which is specifically designed for the task of identifying the readings of word-wheel water meters.

The design objectives of the Meter-YOLOv8n algorithm are twofold: firstly, in real-world scenarios, it aims to improve the detection accuracy of both the complete characters and transitional characters on water meters. Secondly, it seeks to reduce the computational complexity of the algorithm so that it can be deployed in more environments. The network structure of Meter-YOLOv8n is shown in Fig. 1.

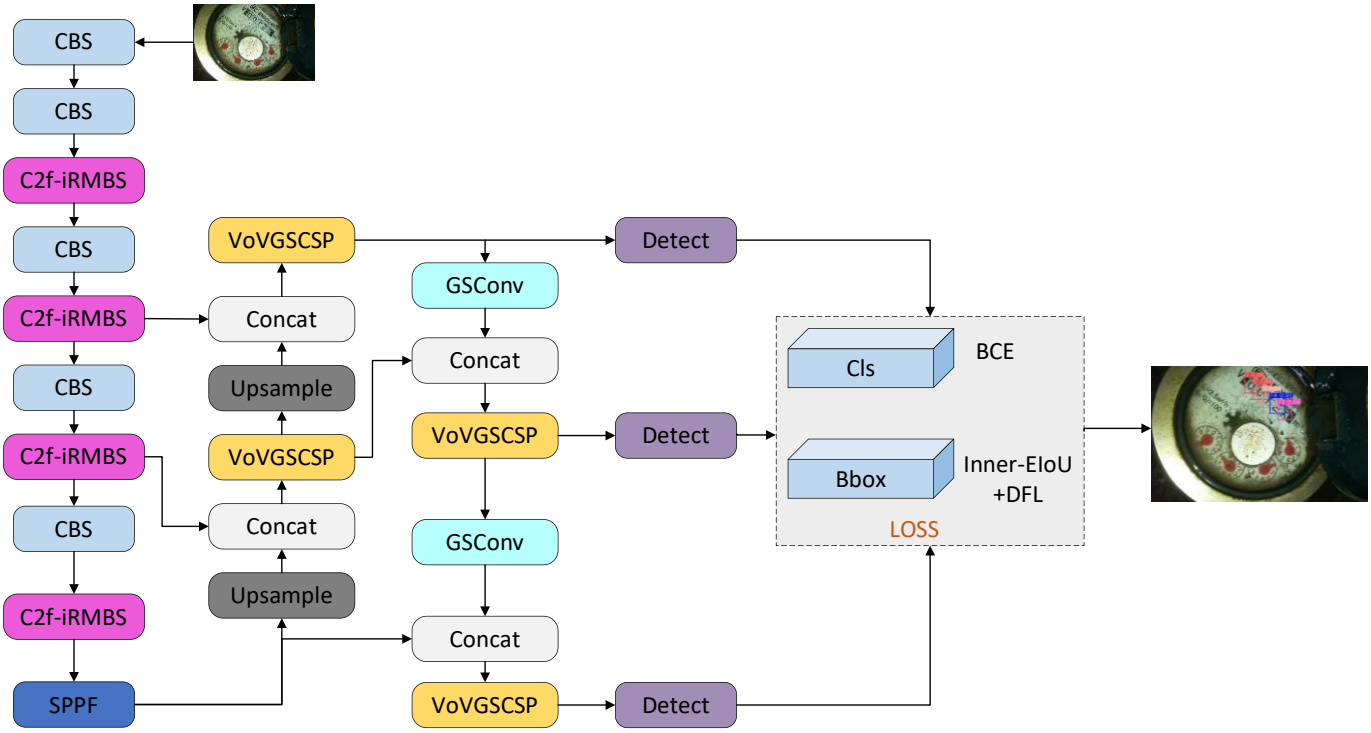



Fig. 1. Network structure of Meter-YOLOv8n.

### B. C2f-iRMBS

*1) iRMB*: In the task of object detection, the attention mechanism can help the algorithm improve its efficiency and accuracy when dealing with complex data. In the images of word-wheel water meters, the background occupies a large proportion, and there are relatively many small object characters that need to be detected. iRMB is a lightweight attention mechanism designed for small object tasks, taking into account the advantages of both dynamic global modeling and static local information fusion. iRMB can better capture the feature information of the objects to adapt to objects of different scales. Moreover, it can effectively increase the receptive field of the model and enhance the model's ability for downstream tasks. The structure of iRMB is shown in Fig. 2.

Firstly, the combined multi-layer perception (CMLP) is used to generate the attention matrices $Q$ and $K$. A dilated

convolution is employed to generate the attention matrix *V*. Then, the window self-attention mechanism is applied to *Q* and *K* for long-range interaction. Immediately afterwards, a depthwise separable convolution (DWConv) is utilized to model the local features. Finally, a compression convolution is used to restore the number of channels, which is then added to the input to obtain the final result.

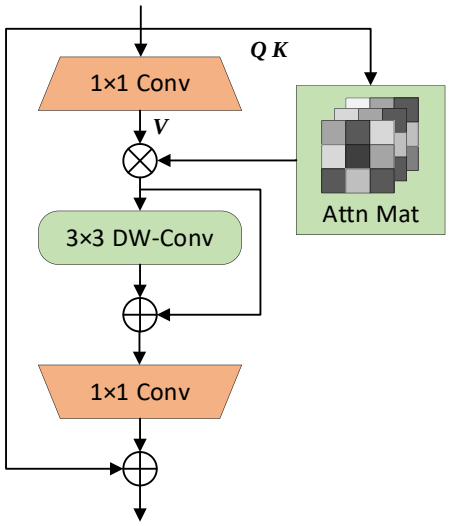
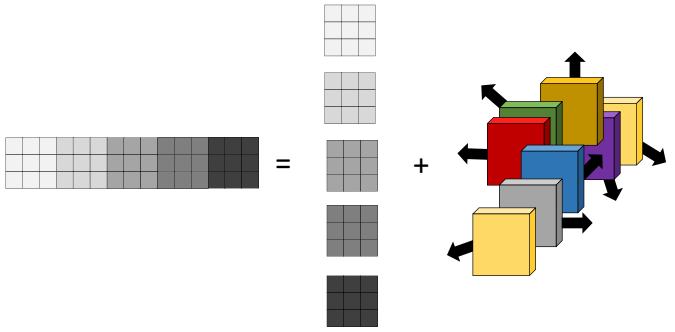
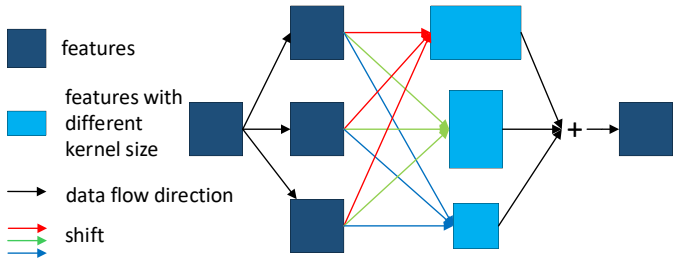



Fig. 2. Structure of iRMB.

*2) Shift-wise conv*: The process of the shift-wise operation is shown in Fig. 3.



(a) The equivalent operation of large-kernel convolution



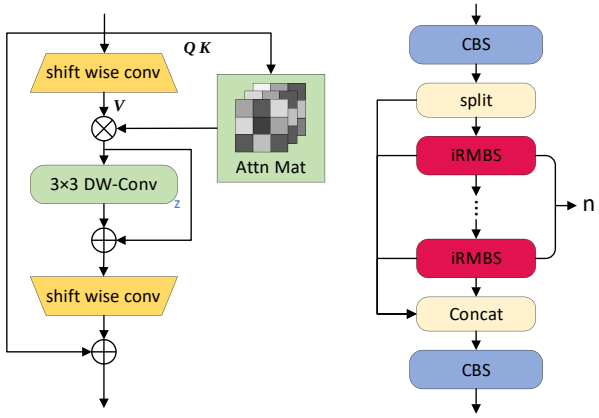

(b) The overall structure of the module

Fig. 3. Schematic diagram of shift-wise conv.

Large-kernel convolution can efficiently capture features in a larger scope, which helps understand the global structure and relationships in the input data. However, the large convolution kernel of large-kernel convolution results in poor ability of the algorithm to process detailed information. Moreover, large-kernel convolution needs to process a larger input data range, so the computational complexity increases, leading to longer training and inference times. To address the above issues, this paper adopts a shift-wise operation. By means of the sparsity mechanism, it ensures that the convolutional neural network (CNN) can capture both long-and short-range dependencies, enabling small convolution kernels to capture global features more efficiently.

*3) C2f-iRMBS*: Word-wheel water meters are often installed underground or in remote corners, and they are affected by unfavorable factors such as dust, light, and water mist. When reading the word-wheel water meters in real-world scenarios, there are problems such as image deformation and the easy loss of object information. Based on iRMB, this paper integrates shift-wise conv to construct a new module, iRMBS, and combines it with C2f to design the novel C2f-iRMBS module, as shown in Fig. 4. In the iRMBS module, shift-wise conv is used to optimize the ordinary convolution, enabling the model to capture global features more efficiently, better learn information such as the scale of the object and the background, and reduce the number of parameters while improving the detection performance.

The improved C2f-iRMBS module is used to replace the C2f in the backbone network, so that the network can correctly capture the key information of the features such as the small size and occlusion of the water meter characters even in complex and changeable real-world scenarios, and it has stronger robustness and generalization ability.




(a) iRMBS (b) C2f-iRMBS

Fig. 4. Structure of C2f-iRMBS.

## C. Slim-Neck Structure

YOLOv8n employs FPN and PAN structures for feature fusion. However, generating multi-scale feature maps using FPN and PAN requires multiple convolution and upsampling operations, which increases computational cost and demands more memory to store these feature maps, ultimately slowing down inference speed. Additionally, FPN and PAN structures can lead to incomplete transmission of feature information across different levels, particularly causing information loss or

blurring during cross-layer information aggregation, which negatively impacts the detection performance for small objects. To reduce model complexity while maintaining accuracy, this paper introduces the Slim-Neck structure in the neck network, replacing the Conv and C2f modules with GSConv and VoVGSCSP modules.

*1) GSConv*: In the neck layer, the GSConv is used. At this stage, the channel dimension $C$ has reached its maximum value, while the height $H$ and width $W$ have reached their minimum values. As a result, there is minimal redundant information, and no compression is needed. The structural diagram of the GSConv is shown in Fig. 5.

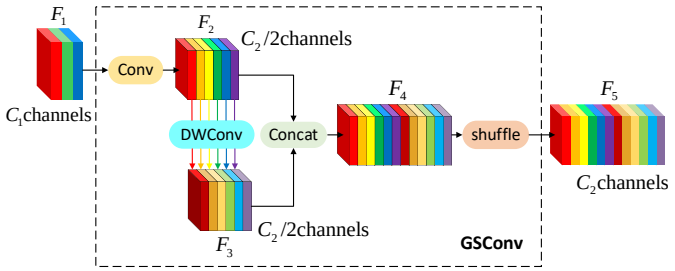



Fig. 5. Structure of GSConv.

In the GSConv, the input feature map $F_1$ undergoes downsampling through a 3×3 convolution to obtain the feature map $F_2$. Then, $F_2$ passes through a depthwise convolution (DWConv) to produce the feature map $F_3$. Next, $F_2$ and $F_3$ are concatenated along the channel dimension to form a new feature map $F_4$. Finally, a Shuffle operation is performed, returning an output $F_5$ with reordered channels. The computation formula for GSConv is shown in Eq. (1).

$$F_{GCS} = Shuffle(Cat(\delta(F_1)_{C_2/2,}\varepsilon(\delta(F_1)_{C_2/2}))_{C_2} \quad (1)$$

In Eq. (1), $F_1$ represents the input feature map with $C_1$ channels, $\delta$ denotes the convolution operation, $\varepsilon$ represents the depth wise convolution operation, and $F_{GCS}$ represents the output feature map with $C_2$ channels obtained through the GSConv.

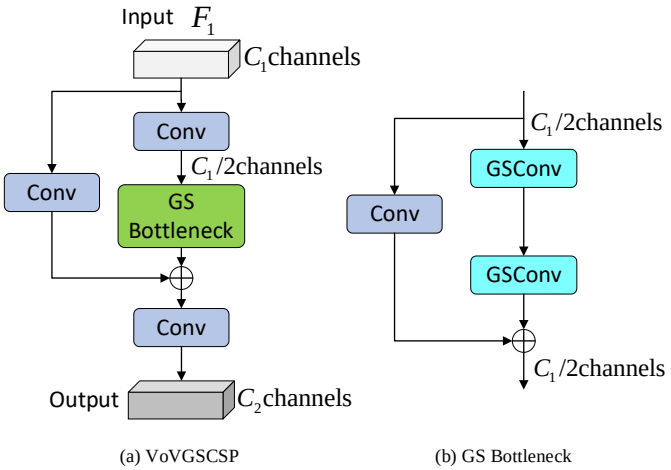
*2) VoVGSCSP*: VoVGSCSP utilizes grouped spatial context supervision to better capture character information at different scales in water meter images, thereby improving detection accuracy. The structure of VoVGSCSP is shown in Fig. 6.

Firstly, a 1×1 conv is applied to the input feature map with a channel size of $C_1$ for feature extraction, reducing the channel dimension to half of the original input. The resulting feature map is then fed into the GS Bottleneck. The GS Bottleneck follows the residual network concept, where the input feature map undergoes two GSConv operations. The output is then concatenated with the feature map obtained through a 1×1 convolution, producing the module's output. Finally, VoVGSCSP concatenates the branch output with the GS Bottleneck output and applies a 1×1 convolution to obtain a feature map with a channel dimension of $C_2$. The computation formula for VoVGSCSP are shown in Eq. (2) and Eq. (3).

$$GSB_{out} = F_{GSC}(F_{GSC}(\alpha(F_1)_{C_2})) + \alpha(F_1)_{C_1/2} \quad (2)$$

$$VoVGSCSP_{out} = \alpha(Concat(GSB_{out}, \alpha(F_1))) \quad (3)$$

In Eq. (2) and Eq. (3), $F_1$ represents the input feature map with $C_1$ channels, $\alpha$ represents the convolution operation, $GSB_{out}$ denotes the output of the GS Bottleneck module, and $VoVGSCSP_{out}$ represents the final output of this module.




(a) VoVGSCSP (b) GS Bottleneck

Fig. 6. Structure of VoVGSCSP.

## D. Inner-EIoU

In the task of recognizing readings from word-wheel water meters, accurately locating water meter characters is essential, including predicting the coordinates of bounding boxes and the positions of center points. Choosing an appropriate bounding box loss function ensures that the model can precisely predict character locations, thereby improving detection accuracy and localization precision.

The YOLOv8n model uses CIoU as the bounding box regression loss function. However, CIoU involves numerous parameters and has a high computational cost, making it less effective in precisely localizing highly overlapping detection boxes. To enhance training efficiency and convergence accuracy, this paper adopts Inner-EIoU as the bounding box regression loss function. Inner-EIoU introduces a scale factor ratio, which controls the size of an auxiliary bounding box for loss computation. The auxiliary bounding box is shown in Fig. 7.

$b^{gt}$ and $b$ represent the ground truth box and the predicted box, respectively. $(x_c^{gt}, y_c^{gt})$ denotes the centroid coordinates of the ground truth box, $(x_c, y_c)$ denotes the centroid coordinates of the predicted box. $w^{gt}$ and $h^{gt}$ represent the width and height of the ground truth box, respectively, while $w$ and $h$ represent the width and height of the predicted box, respectively.

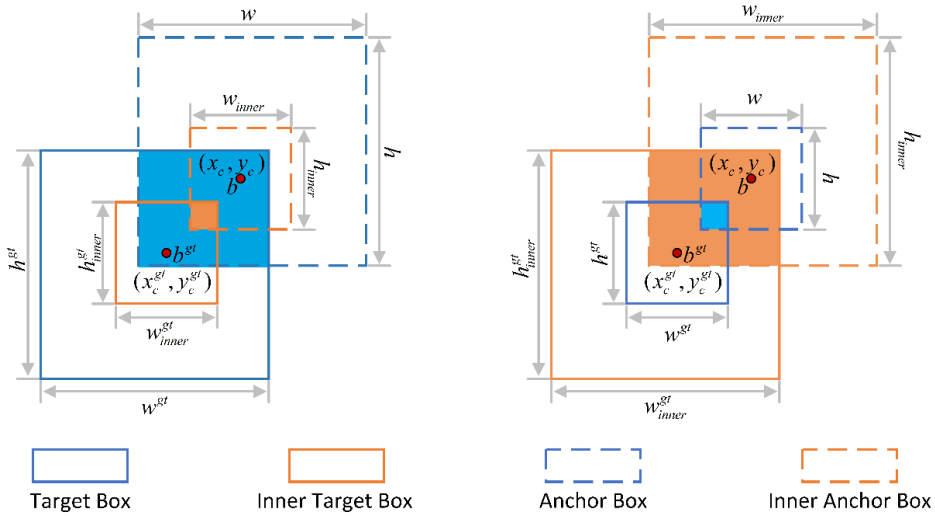



Fig. 7. Auxiliary bounding box drawing.

The calculation formula of Inner-EIoU is shown in Eq. (4).

$$L_{Inner-EIoU} = L_{EIoU} + IoU - IoU^{inner} \tag{4}$$

In Eq. (4), $L_{EIoU}$ represents the EIoU loss function, IoU represents the intersection over union ratio between the predicted bounding box and the ground truth bounding box, and the definition of $IoU^{inner}$ is shown in Eq. (5).

$$IoU^{inner} = \frac{inter}{union} \tag{5}$$

The ratio is the scale factor for generating the auxiliary bounding box, and its value range is usually [0.5, 1.5]. The definitions of *inter* and *union* are shown in Eq. (6) and Eq. (7).

$$\begin{aligned} inter = &\left(\min\left(b_r^{gt}, b_r\right) - \max\left(b_l^{gt}, b_l\right)\right) \\ &*\left(\min\left(b_b^{gt}, b_b\right) - \max\left(b_t^{gt}, b_t\right)\right) \end{aligned} \tag{6}$$

$$\begin{aligned} union = &\\ &\left(w^{gt} * h^{gt}\right) * (ratio)^2 + (w * h) * (ratio)^2 - inter \end{aligned} \tag{7}$$

The definitions of $b_l^{gt}$, $b_r^{gt}$, $b_t^{gt}$, $b_b^{gt}$, $b_l$, $b_r$, $b_t$ and $b_b$ are shown in Eq. (8) to Eq. (11).

$$b_l^{gt} = x_c^{gt} - \frac{w^{gt} * ratio}{2}, b_r^{gt} = x_c^{gt} + \frac{w^{gt} * ratio}{2} \tag{8}$$

$$b_t^{gt} = y_c^{gt} - \frac{h^{gt} * ratio}{2}, b_b^{gt} = y_c^{gt} + \frac{h^{gt} * ratio}{2} \tag{9}$$

$$b_l = x_c - \frac{w * ratio}{2}, b_r = x_c + \frac{w * ratio}{2} \tag{10}$$

$$b_t = y_c - \frac{h * ratio}{2}, b_b = y_c + \frac{h * ratio}{2} \tag{11}$$

Inner-EIoU takes into account not only the overlapping area but also geometric information such as the distance and angle between the predicted bounding box and the ground truth bounding box. This enables the model to adjust the position and orientation of the predicted bounding box more precisely during the training process, improving the detection accuracy for small objects, dense objects, and objects with irregular shapes.

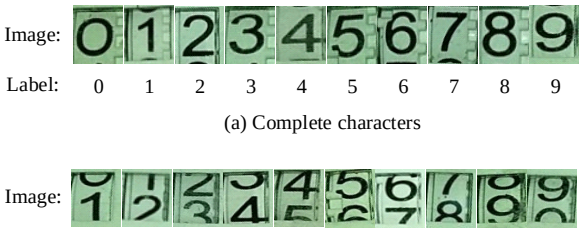
## IV. Dataset and Experimental Design

### A. Dataset

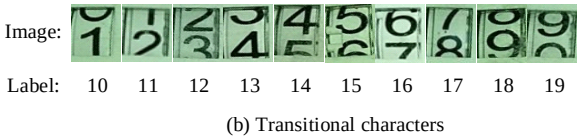
In this experiment, the dataset publicly available in the CCF Big Data and Computational Intelligence Contest is adopted. It is named the Automatic Water Meter Reading dataset in Real-world Scenarios. To improve the generalization ability of the dataset, and while ensuring that the water meter reading area can be recognized, this paper uses seven different data augmentation methods combined randomly to enhance the images in the dataset. The seven data augmentation methods used in the experiment are: 1) adding Gaussian noise; 2) changing the color temperature; 3) setting random brightness; 4) applying Gaussian blur; 5) random cropping and padding; 6) random rotation between -45° and +45°; 7) random scaling. The augmented dataset consists of a total of 3680 images with a size of 960×540 pixels. Some images from the dataset are shown in Fig. 8.

We used the LabelImg image annotation software to annotate the valid characters in water meter images. During the annotation process, we observed that the characters in the reading area might be in a transitional state. To achieve more precise readings, we introduced 10 new labels to represent transitional characters based on the complete characters. The annotated content includes 20 labels, ranging from "0" to "19", where "0 to 9" represent complete characters and "10 to 19" represent transitional characters. The individual characters of the water meter and their corresponding labels are shown in Fig. 9. The dataset was divided into training, testing, and validation sets in a 7:1:2 ratio for the experiments.

Fig. 8. Example diagram of the dataset.




(a) Complete characters




(b) Transitional characters

Fig. 9. The label corresponding to a single character in the dataset.

### B. Evaluation Metrics

In the experiment of this paper, precision (P), recall (R), mAP@0.5 and mAP@0.5:0.95 are used to measure the reading recognition performance of the improved algorithm for the word-wheel water meter.

Precision refers to the proportion of actual positive samples among all the samples predicted as positive. Recall refers to the proportion of samples that are correctly predicted as positive among all the actual positive samples. The calculation formulas are shown in Eq. (12) and Eq. (13).

$$P = \frac{TP}{TP + FP} \tag{12}$$

$$R = \frac{TP}{TP + FN} \tag{13}$$

TP(True positive) represents the number of samples that are actually positive and predicted as positive, FP(false positive) represents the number of samples that are actually negative but predicted as positive, and FN(false negative) represents the number of samples that are actually positive but predicted as negative.

mAP represents the mean average precision. mAP@0.5 is calculated by computing the average precision of each category when the Intersection over Union (IoU) threshold is 0.5, and then taking the average of the average precisions of all categories. mAP@0.5:0.95 represents the average mAP at different IoU thresholds (ranging from 0.5 to 0.95 with a step size of 0.05), which is used to evaluate the detection performance of the model. The higher the mAP value is, the better the performance of the algorithm in the task of identifying the word-wheel water meter. The calculation formula are shown in Eq. (14) and Eq. (15).

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{14}$$

$$AP_i = \int_0^1 P_i(R)d(R) \tag{15}$$

FLOPs (Floating-Point Operations) refer to the number of floating-point operations, which is an important indicator for measuring the computational complexity and computational workload of deep learning models. Through the value of FLOPs, one can intuitively understand the computational complexity of the model. The larger the FLOPs value is, it indicates that the model needs to perform more floating-point operations during operation, the computational cost is higher, and it may require more computational resources and longer computation time.

### C. Experimental Environment

The CPU of the experimental operating environment is an Intel(R) Xeon(R) Platinum 8255C 2.50GHz 12-core processor, with 43GB of memory. The GPU is an NVIDIA RTX 3090, and the video memory is 24GB. The operating system is Ubuntu 20.04, and the acceleration environment is CUDA 11.3. The programming language is Python 3.8, and the deep learning framework is Pytorch 1.11.0. The experimental parameter settings are shown in Table I:

TABLE I. PARAMETERS OF THE EXPERIMENT

| Parameter Name | Parameter Value |
|---|---|
| Input resolution | 640×640 |
| Epochs | 230 |
| Batch size | 8 |
| Initial learning rate (Lr0) | 0.01 |
| Weight_decay | 0.0005 |

## V. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the effectiveness of the improved algorithm, this paper conducts comparative experiments and ablation experiments on the dataset of word-wheel water meters. During the training process, the same experimental equipment and experimental parameters are adopted, and the obtained experimental results are compared and analyzed.

### A. Performance Comparison Before and After the Algorithm Improvement

In this paper, the original YOLOv8n algorithm and the improved algorithm Meter-YOLOv8n were used to train on the same dataset of word-wheel water meters, resulting in the YOLOv8n model and the Meter-YOLOv8n model. The

changing trends of various evaluation indicators during the training process are shown in Fig. 10. Compared with the YOLOv8n model, the improved Meter-YOLOv8n model has improvements in multiple evaluation indicators, which proves the superiority of the Meter-YOLOv8n model.

As can be seen from Fig. 10, the improved model converges faster, indicating that the improved module effectively reduces the computational cost and resource consumption. The design of the improved model structure is more reasonable, enabling the model to perform better in the task of identifying the readings of word-wheel water meters. Compared with the original model, the improved model has improvements in precision, recall, and mAP, and the improved model also converges faster.

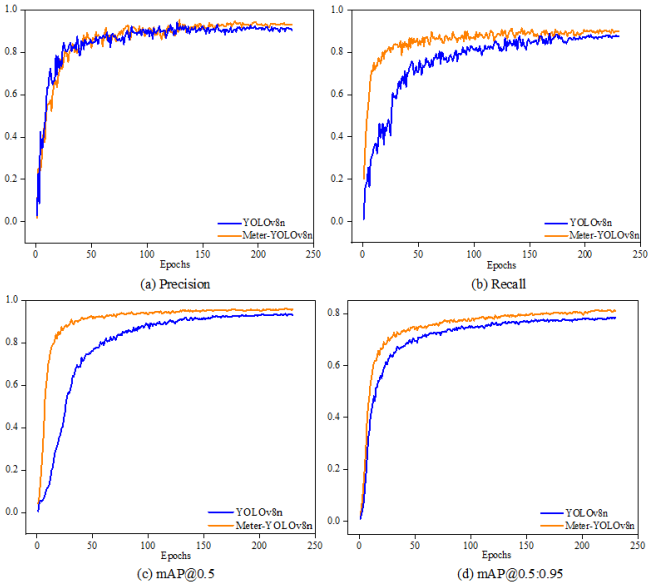



Fig. 10. The changing trends of various indicators before and after the algorithm improvement.

In order to explore the specific improvements of the improved model on the complete characters and transitional characters in the dataset, an experimental comparison is conducted between the improved model and the original YOLOv8n model. The experimental results of these two models on the test dataset of word-wheel water meters are shown in Table II.

TABLE II. TEST RESULTS OF THE MODEL BEFORE AND AFTER THE IMPROVEMENT

| Model | Class | P(%) | R(%) | mAP@ 0.5(%) | mAP@ 0.5:0.95(%) |
|---|---|---|---|---|---|
| **YOLOv8n** | Complete characters | 95.5 | 88.6 | 95.3 | 81.5 |
| | Transitional characters | 91.9 | 85.8 | 90.5 | 74.1 |
| | All | 93.7 | 87.2 | 92.9 | 77.8 |
| **Meter-YOLOv8n** | Complete characters | 96.1 | 90.2 | 97.0 | 83.5 |
| | Transitional characters | 94.7 | 88.0 | 95.6 | 76.7 |
| | All | 95.4 | 89.1 | 96.3 | 80.1 |

Table II compares the performance of the model before and after the improvement. Based on the experimental results of the two categories, namely complete characters and transitional characters, it can be concluded that the improved model has improvements in all indicators. The mAP@0.5 and mAP@0.5:0.95 of complete characters have increased by 1.7% and 2.0% respectively, while the mAP@0.5 and mAP@0.5:0.95 of transitional characters have increased by 5.1% and 2.6% respectively. The improvement range of various indicators of transitional characters is relatively large, indicating that the improved model has enhanced the expressive ability for transitional characters.

### *B. Comparative Experiments of the C2f Module*

In order to improve the feature extraction ability of the backbone network and simplify the feature extraction process, this paper proposes several different improvement schemes for the C2f module, which are as follows: 1) Use the original C2f module. 2) Replace the convolution module in the Bottleneck structure of C2f with ODConv, named C2f-ODConv. 3) Add the attention mechanism in CloFormer that fuses global and local features to the Bottleneck of C2f, named C2f-CloAtt. 4) Integrate SCConv into the C2f module, named C2f-SCConv. 5) Replace the Bottleneck in C2f with Dilated Re-parameterized Block module from UniRepLKNet, named C2f-DRB. 6) Replace the Bottleneck in C2f with the Diverse Branch Block, named C2f-DBB. 7) Introduce the Faster Block module into the C2f module, named C2f-Faster. 8) Combine the iRMB attention mechanism and shift-wise conv to obtain the lightweight C2f-iRMBS module, and replace the Bottleneck structure in C2f with it, named C2f-iRMBS. These improvement strategies are trained using the same dataset under the same experimental environment. The experimental results are shown in Table III.

TABLE III. EXPERIMENTAL RESULTS OF DIFFERENT C2F MODULES

| Model | mAP@0.5(%) | Params(M) | FLOPs(G) |
|---|---|---|---|
| C2f | 92.9 | 3.15 | 8.7 |
| C2f-ODConv [26] | 92.3 | 3.07 | 5.8 |
| C2f-CloAtt [27] | 94.7 | 3.77 | 9.3 |
| C2f-SCConv [28] | 93.6 | 3.96 | 9.5 |
| C2f-DRB [29] | 90.6 | 2.60 | 6.4 |
| C2f-DBB [30] | 93.1 | 4.28 | 11.2 |
| C2f-Faster [31] | 94.2 | 2.71 | 6.7 |
| C2f-iRMBS | 94.4 | 2.72 | 6.7 |

As can be seen from Table III, C2f-ODConv significantly reduces the computational complexity and improves the computational efficiency. However, the mAP@0.5 drops by 0.6%, indicating that C2f-ODConv needs to strike a balance between computational complexity and mAP. C2f-CloAtt increases the mAP@0.5 to 94.7%, but the FLOPs increase significantly, raising the requirements for computational resources. C2f-SCConv improves the mAP of the model, but it also suffers from the problem of excessive reliance on computational resources, which is not conducive to practical

applications. C2f-DRB reduces the FLOPs, but the mAP@0.5 also drops, degrading the detection performance of the model. C2f-DBB has excessively high computational complexity and FLOPs, with mediocre overall performance. Both C2f-Faster and C2f-iRMBS improve the mAP of the model and reduce the number of parameters and FLOPs. This proves that C2f-Faster and C2f-iRMBS can well balance the relationship between computational complexity and mAP. Compared with other improvement strategies, C2f-iRMBS increases the mAP by 1.5% and reduces the number of parameters and FLOPs by 0.43M and 2.0G respectively. It can improve the detection accuracy and efficiency of word-wheel water meters and is more suitable for the task of word-wheel water meter reading recognition.

### C. Comparative Experiments of different Loss Functions

In order to verify the impact of different loss functions on the model's detection performance, this paper conducts comparative experiments using models with several bounding box loss functions, namely CIoU, SIoU, EIoU, and Inner-EIoU. The ratio values of Inner-EIoU are set to 0.7, 0.8, 0.9, and 1.1 respectively. The experimental results are shown in Table IV.

TABLE IV. EXPERIMENTAL RESULTS OF DIFFERENT LOSS FUNCTIONS

| Loss function | ratio | P/% | R/% | mAP@0.5/% |
|---|---|---|---|---|
| CIoU | - | 93.7 | 87.9 | 92.9 |
| SIoU | - | 93.6 | 86.5 | 92.6 |
| EIoU | - | 94.0 | 88.1 | 93.1 |
| Inner-EIoU | 0.7 | 94.3 | 88.2 | 93.2 |
| Inner-EIoU | 0.8 | 94.6 | 88.3 | 93.3 |
| Inner-EIoU | 0.9 | 94.7 | 88.6 | 93.7 |
| Inner-EIoU | 1.1 | 94.4 | 88.2 | 93.4 |

From the experimental results in Table IV, it can be seen that when Inner-EIoU is selected as the loss function of the model, the detection performance is the best. When the ratio is set to 0.9, precision, recall, and mAP@0.50 achieve the optimal values. Therefore, Inner-EIoU is selected as the bounding box loss function in this paper, and the ratio is set to 0.9.

### D. Ablation Experiment

In order to verify the contribution of the improved module to the improved model, an ablation experiment was conducted on the dataset of word-wheel water meters. By gradually introducing the improved module and evaluating the performance of the model, the results of the ablation experiment are shown in detail in Table V. YOLOv8n represents the baseline model. YOLOv8n-C represents YOLOv8n + C2f-iRMBS. YOLOv8n-S represents YOLOv8n + Slim-Neck. YOLOv8n-CS means YOLOv8n + C2f-iRMBS + Slim-Neck. Meter-YOLOv8n represents YOLOv8n + C2f-iRMBS + Slim-Neck + Inner-EIoU.

The baseline model, YOLOv8n, achieves a precision of 93.7%, a recall of 87.9%, a mAP@0.5 of 92.9%, and a mAP@0.5:0.95 of 76.8%. It has 3.15M parameters, 8.7G FLOPs, a model size of 6.3M, and an FPS of 83 F/S. Overall, its performance is average. After introducing C2f-iRMBS, mAP@0.5 and mAP@0.5:0.95 improved by 1.5% and 0.7%, respectively, while the number of parameters and FLOPs decreased by 0.43M and 2.0G, respectively. This indicates that C2f-iRMBS enhances the detection performance by capturing richer character feature maps through branch structures and shift operations while reducing model parameters and computational cost.

With the Slim-Neck structure improving the neck network, mAP@0.5 and mAP@0.5:0.95 increased by 1.2% and 0.4%, respectively, while parameters and FLOPs decreased by 0.14M and 1.6G, respectively. This suggests that Slim-Neck effectively integrates features across different scales and levels, improving detection efficiency.

When both C2f-iRMBS and Slim-Neck are introduced simultaneously, mAP@0.5 and mAP@0.5:0.95 increased by 3.0% and 2.8%, respectively, while parameters and FLOPs decreased by 0.57M and 2.6G, demonstrating their strong compatibility. This enables the model to better balance detection performance and computational cost.

By integrating all modules, the resulting Meter-YOLOv8n model achieves an accuracy of 95.4%, a recall of 89.1%, a mAP@0.5 of 96.3%, and a mAP@0.5:0.95 of 80.1%. It has 2.59M parameters, 6.1G FLOPs, a model size of 5.6M, and an FPS of 87 F/S. Experimental results confirm that Meter-YOLOv8n enhances the detection performance of word-wheel water meters while maintaining a lightweight design, with each improvement module playing a positive role.

TABLE V. RESULTS OF ABLATION EXPERIMENT

| Model | P (%) | R (%) | mAP@0.5 (%) | mAP@0.5:0.95 (%) | Params (M) | FLOPs (G) | Size (MB) | FPS (F/S) |
|---|---|---|---|---|---|---|---|---|
| YOLOv8n | 93.7 | 87.9 | 92.9 | 76.8 | 3.15 | 8.7 | 6.3 | 83 |
| YOLOv8-C | 94.7 | 88.2 | 94.4 | 77.5 | 2.72 | 6.7 | 5.8 | 85 |
| YOLOv8n-S | 94.1 | 88.0 | 94.1 | 77.2 | 3.05 | 8.1 | 6.1 | 84 |
| YOLOv8n-CS | 95.3 | 89.1 | 95.9 | 79.6 | 2.58 | 6.1 | 5.6 | 87 |
| Meter-YOLOv8n | 95.4 | 89.1 | 96.3 | 80.1 | 2.59 | 6.1 | 5.6 | 87 |

### E. Comparative Experiment

To verify the detection performance of the improved algorithm on the word-wheel water meter, the improved algorithm was compared with the currently popular single-stage and two-stage algorithms, specifically including Faster R-CNN, DETR, YOLOv3, YOLOv4, YOLOv5s, YOLOv7-tiny, YOLOv8s, YOLOv8n, YOLOv10n and YOLOv11n. The comparison results are shown in Table VI.

According to the experimental results in Table VI, the number of parameters, FLOPs, and model size of the Faster R-CNN, YOLOv3, and DETR algorithms are too large, and their detection performance is mediocre. Therefore, their application in real-world scenarios is somewhat limited. The YOLOv4 algorithm has relatively high computational complexity and requires more computational resources, so it is not suitable for the task of word-wheel water meter reading recognition. The YOLOv7-tiny algorithm strikes a balance among performance, computational load, and model size, but its overall performance is just average. YOLOv5s and YOLOv8n have similar performance, but the model size and computational load of YOLOv5s are larger than those of YOLOv8n. The YOLOv10n and YOLOv11n algorithms have fewer parameters and FLOPs, but their detection performance is not satisfactory. The recognition accuracy and mAP of YOLOv8s are slightly higher than those of YOLOv8n, but its model size is more than three times that of YOLOv8n, leading to difficulties in deployment. Compared with other models, Meter-YOLOv8n has the highest mAP. Although its number of parameters is slightly higher than that of YOLOv10n, its FLOPs and model size are lower. Thus, it can quickly and accurately read the readings of word-wheel water meters in resource - constrained environments.

TABLE VI. RESULTS OF COMPARATIVE EXPERIMENT

| Model | P (%) | R(%) | mAP@0.5 (%) | mAP@0.5:0.95 (%) | Params (M) | FLOPs (G) | Size (MB) | FPS (F/S) |
|---|---|---|---|---|---|---|---|---|
| Faster R-CNN | 92.8 | 86.1 | 90.9 | 75.7 | 43.95 | 133.6 | 106.2 | 37 |
| DETR [32] | 93.5 | 86.9 | 92.3 | 76.8 | 42.30 | 122.3 | 113.3 | 38 |
| YOLOv3 [33] | 82.3 | 73.1 | 85.6 | 69.7 | 10.33 | 45.6 | 78.6 | 45 |
| YOLOv4 [34] | 92.9 | 86.1 | 91.1 | 76.2 | 9.96 | 33.7 | 32.9 | 65 |
| YOLOv5s | 93.8 | 87.7 | 92.9 | 77.1 | 9.12 | 23.2 | 18.6 | 72 |
| YOLOv7-tiny | 92.6 | 86.0 | 90.7 | 75.6 | 6.01 | 12.8 | 14.1 | 75 |
| YOLOv8s | 94.0 | 88.1 | 93.1 | 77.1 | 11.1 | 28.5 | 42.1 | 62 |
| YOLOv8n | 93.7 | 87.9 | 92.9 | 76.8 | 3.15 | 8.7 | 6.3 | 83 |
| YOLOv10n [35] | 92.1 | 85.6 | 90.3 | 75.3 | 2.58 | 7.8 | 5.9 | 85 |
| YOLOv11n [36] | 92.0 | 85.3 | 90.1 | 74.9 | 2.60 | 6.3 | 5.8 | 85 |
| Meter-YOLOv8n | 95.4 | 89.1 | 96.3 | 80.1 | 2.59 | 6.1 | 5.6 | 87 |

### F. Visual Analysis

*1) Dataset visualization*: The label distribution diagram after training on the word-wheel dataset is shown in Fig. 11.

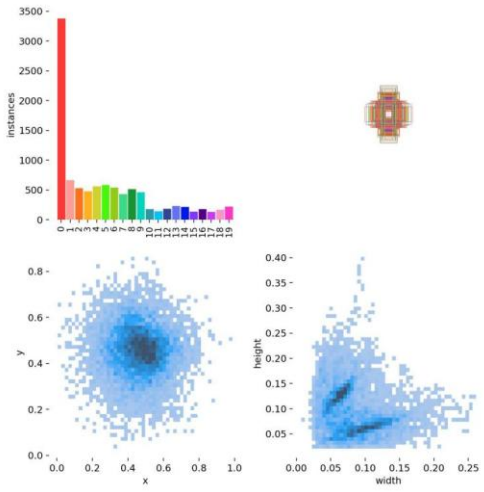



Fig. 11. Dataset visualization.

From the bar chart, it can be seen that the number of samples in the "0" category is the largest, exceeding 3000. The number of samples of complete characters "1 to 9" is around 500, and the number of samples of transitional characters "10 to 19" is relatively small, approximately 250. From the x-y density plot and the width - height density plot, it can be seen that most of the object center points are concentrated near (0.5, 0.5), forming an obvious dense area and exhibiting the characteristics of a Gaussian distribution. The width and height of most objects are relatively small, concentrated between 0.05 and 0.15. From the overlapping box plot, it can be seen that most of the objects are located in the central area of the image, and the distribution of the bounding boxes is relatively symmetric.

*2) Heatmap visualization*: In order to more precisely observe the degree of attention paid by the model to the effective characters of the water meter before and after the improvement, this paper uses Gradient-weighted Class Activation Mapping (Grad-CAM) to generate heatmaps for the YOLOv8n model and the improved model Meter-YOLOv8n. Grad-CAM plays a crucial role in the field of model interpretability. It enables researchers to determine whether the

model accurately focuses on the correct image features related to the recognition of water meter readings when processing images. By observing the different colored areas in the heatmaps, we can determine the contribution degree of different regions in the water meter image to the prediction results. The red and yellow areas indicate a higher contribution degree to the prediction results, the green areas indicate a lower contribution degree to the prediction results, and the blue areas indicate no contribution to the prediction results. The heatmaps before and after the model improvement are shown in Fig. 12.

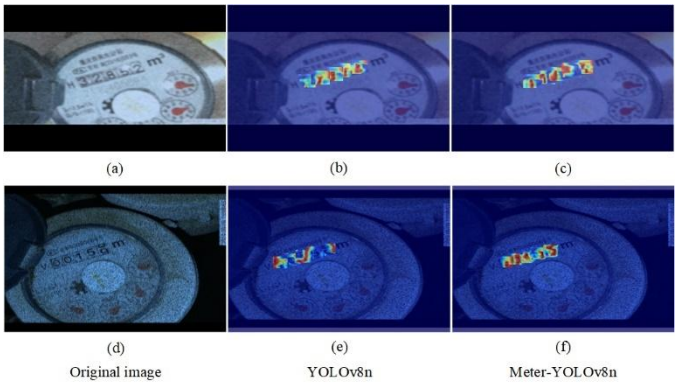



Fig. 12. Heatmap visualization.

By comparing Fig. 12(b) and Fig. 12(c), it can be seen that the YOLOv8n model pays more attention to the edge information of the effective characters, which leads to a decrease in the recognition accuracy of the water meter by the model. As shown in Fig. 12(e), when the water meter image is affected by noise, the YOLOv8n model reduces its attention to the effective characters, and the blue area accounts for a relatively large proportion, resulting in situations of missed detection and false detection by the model. As shown in Fig. 12(f), the improved model focuses more on the character information on the dial and suppresses the interference of other invalid characters on the dial. By observing the heatmap generated by Grad-CAM, it can be known that, compared with the YOLOv8n model, the image areas that the improved model focuses on when making decisions are more comprehensive, which improves its detection ability for complete characters and transitional characters.

*3) Results visualization*: In order to more intuitively demonstrate the detection performance and generalization ability of the improved model, models with relatively good comprehensive performance are used to conduct inference verification on the validation set of word-wheel water meters. These models include YOLOv7-tiny, YOLOv10n, YOLOv8n, YOLOv8s, and the improved model Meter-YOLOv8n. The visualization of the experimental results is shown in Fig. 13.

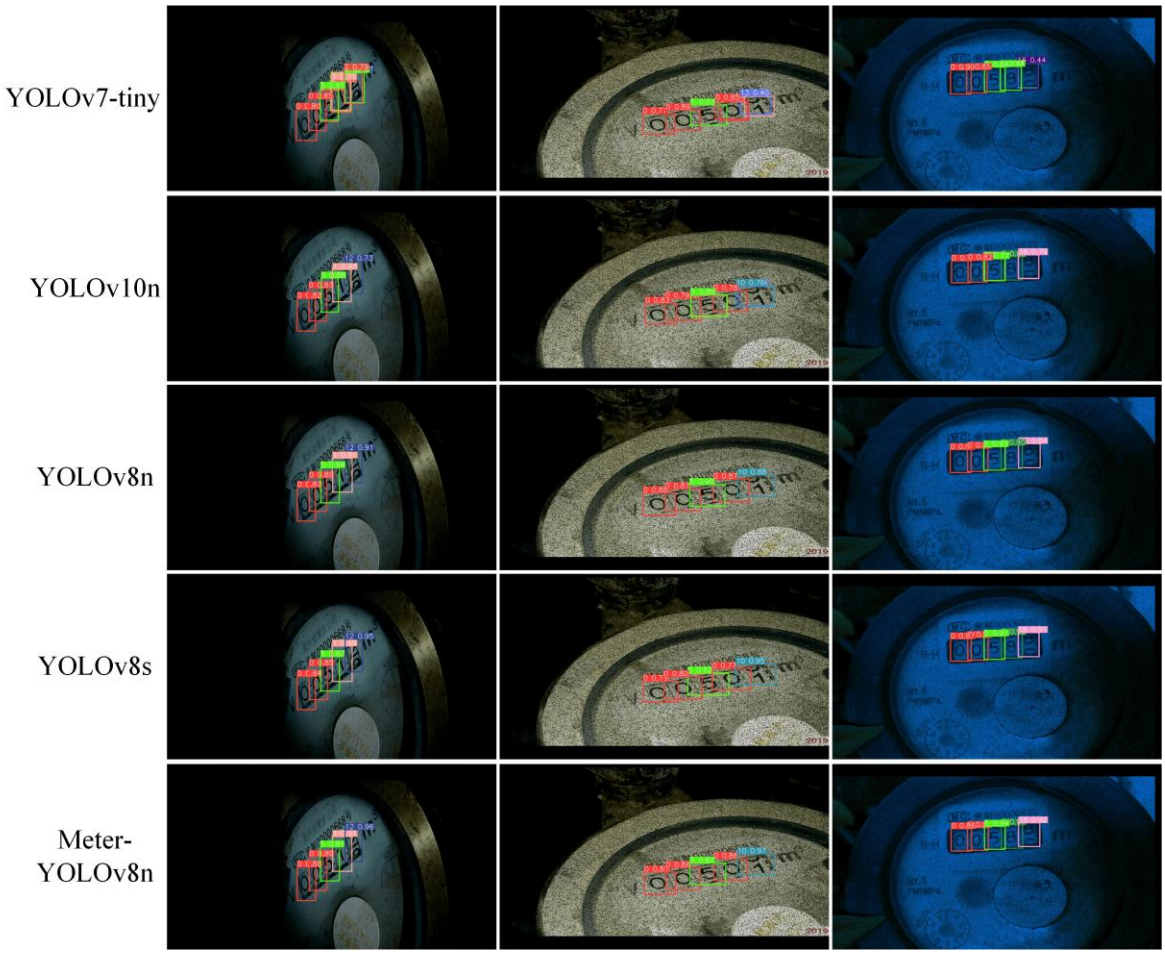



Fig. 13. Result visualization.

In the absence of interference, YOLOv7-tiny and YOLOv10n can correctly recognize the complete characters on the word-wheel water meter, but they perform poorly in recognizing transitional characters. When the image is affected by unfavorable factors such as lighting and noise, the recognition accuracy of YOLOv7-tiny and YOLOv10n drops significantly, and YOLOv7-tiny experiences false detections and repeated detections. YOLOv10n, YOLOv8n, and YOLOv8s can accurately recognize both the complete characters and transitional characters of the water meter in an interference-free environment. However, when the image is affected by environmental interference, the recognition accuracy of these models for characters decreases, especially for transitional characters. The improved model Meter-YOLOv8n can accurately recognize both the complete characters and transitional characters of the word-wheel water meter in different environments, and it has the highest recognition accuracy, fully verifying the detection performance and generalization ability of the improved model Meter-YOLOv8n.

## VI. Conclusion

This paper proposes a high-accuracy and lightweight word-wheel water meter reading recognition model, Meter-YOLOv8n, and introduces multiple improvements tailored to the characteristics of water meter images. The C2f-iRMBS module is introduced to replace the original C2f, simplifying the feature extraction network while enhancing the model's ability to extract character information from water meters. To address the challenges of small object features being indistinct and highly similar to the background in water meter images, a Slim-Neck module is incorporated to enhance multi-scale feature fusion of small objects, thereby improving detection accuracy. Additionally, the Inner-EIoU loss function replaces the original CIoU loss function, enhancing the performance of bounding box regression. Through comparative experiments, ablation studies, and visualization analysis, the improved model achieves a 3.4% increase in mAP@0.5 compared to the original model, while reducing the number of parameters by 0.56M and FLOPs by 2.6G. The proposed improvements achieve a better balance between detection accuracy and model complexity. The Meter-YOLOv8n model has improved the recognition accuracy of word-wheel water meters while reducing the computational load and model size. It is more in line with the characteristics of edge devices, which have limited resources but require high detection accuracy. This has laid a solid foundation for its deployment on edge devices.

In future work, we will collect more images of word-wheel water meters from different brands and environments, and increase the number of transitional characters in the dataset. We will take the actual deployment on low-power edge hardware such as Raspberry Pi or NVIDIA Jetson Nano.

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# Optimization Design of Robot Grasping Based on Lightweight YOLOv6 and Multidimensional Attention

Junyan Niu*, Guanfang Liu
Henan College of Transportation, Zhengzhou 450000, China

***Abstract*—To address the computational redundancy and robustness limitations of industrial grasping models in complex environments, this study proposes a lightweight capture detection framework integrating Mobile Vision Transformer (MobileViT) and You Only Look Once version 6 (YOLOv6). Three innovations are developed: 1) A cascaded architecture fusing convolution and Transformer to compress parameters; 2) A multidimensional attention mechanism combining channel-pixel dual enhancement; 3) A Pixel Shuffle-Receptive Field Block (PixShuffle-RFB) decoder enabling sub-pixel localization. Experiments demonstrate that the model achieves 0.88 detection accuracy with 66 Frames Per Second (FPS) in simulations and 90.04% grasping success rate in physical tests. The lightweight design reduces computational costs by 37% versus conventional models while maintaining 93.54% segmentation efficiency (2.85 milliseconds inference). This multidimensional attention-driven approach effectively improves industrial robot adaptability, advancing capture detection applications in high-noise manufacturing scenarios.**

***Keywords*—Capture detection; YOLOv6; multidimensional attention; MobileViT; industrial robot; lightweight**

## I. Introduction

With the rapid growth of demand for industrial production automation, robots have become a key force driving productivity leaps and factory automation. Robot grasping detection technology combines machine vision with robots, and can improve object recognition and grasping efficiency on the production line through intelligent algorithms. According to the differences in grasping algorithm logic, robot grasping detection can be broken into rule-based grasping design and learning-based grasping design [1]. Rule-based grasping detection utilizes geometric models and physical properties to determine the optimal grasping point by analyzing object shape and force closure conditions [2]. Learning-based grasping detection relies on a large amount of data training to automatically learn object features and grasping strategies, adapting to unknown objects and complex environments [3]. However, with the increasingly complex production environment and processing tasks, traditional robot grasping and detection methods are no longer able to meet practical needs. For example, support vector machines have low efficiency in processing large-scale data and poor detection accuracy for complex shaped objects [4]. The random forest decision tree model is too large, resulting in poor real-time performance and making it difficult to deploy applications on embedded devices [5]. Gaussian mixture models are sensitive to initial parameters, have long training times, and are difficult to quickly adapt to environmental changes [6]. These issues seriously affect the accuracy and real-time performance of robot grasping. Therefore, the current industrial grasp detection faces a dual challenge: 1) the traditional model has insufficient feature discriminative power under complex background interference, leading to the accumulation of localization bias; 2) there is a significant contradiction between real-time detection demand and model computational load, and it is difficult for the existing methods to balance accuracy and efficiency. This restricts the ability of automated production lines to efficiently process shaped workpieces, and there is an urgent need to establish a new paradigm of lightweight and highly robust gripping detection.

In response to the above challenges, starting from the effective acquisition of object position and optimization of grasping pose, the research focuses on the basic logic and problems of single-stage real-time object detection algorithm You Only Look Once Version 6 (YOLOv6) and Multi-Dimensional Attention Fusion Network (MDAFN) modules, and improves them by proposing a Lightweight YOLOv6 with MDAFN for Robotic Grasping Detection (L-YOLOv6-MA). The research aims to: 1) establish a lightweight feature extraction framework to solve the contradiction between real-time performance and accuracy of traditional models; 2) strengthen the feature discrimination ability for the complex texture interference problem; 3) realize sub-pixel level grasping bit-position estimation to provide an end-to-end solution with both high accuracy and low latency for dynamic industrial scenes. The innovations of the research are: 1) establishing Mobile Vision Transformer (MobileViT) and YOLOv6 hybrid architecture, realizing the complementary advantages of MobileViT and YOLOv6; 2) designing the channel-space dual-domain attention mechanism to enhance the physical-semantic correlation of feature representations; 3) developing a multi-scale receptive field decoder to overcome the problem of dynamic balance between the local features of the grasping point and the global context information, and providing a solution for industrial inspection and detection. The research is structured into four sections. The first section introduces the current research on the logic and algorithms of robot grasping detection worldwide. The second section starts from modules such as YOLOv6 and MDAFN to establish a precise and real-time robot grasping detection model. The third section provides numerical examples and practical application analysis of the proposed algorithm model to verify its reliability. The final

*Corresponding Author

section provides a comprehensive summary and analysis of the article.

## II. Related Works

With the quick growth of information technology and the scaling up of various industries, the application of robots in fields such as workshop transportation and assembly line processing is showing a rapidly increasing trend. Robot grasping detection is the core of achieving factory automation and fine operations, and it is also an important application direction that smart industry needs to continuously expand and deepen. However, in practical work, the performance of robot grasping detection for complex tasks is not stable, so many researchers are improving this problem. Wang S et al. raised a Transformer-based robot vision grasping model for object feature capture and long-range dependency modeling. By combining local window attention mechanism to obtain local contextual information, the model could simultaneously handle local information and long-range visual concept relationships in complex scenes [7]. In response to the demand for grasping posture and quality evaluation in robot grasping tasks, Yu S et al. proposed a novel squeeze excitation residual U-shaped network, which combines residual blocks with channel attention mechanism to generate grasping postures and predict the quality score of each posture, improving grasping accuracy and time efficiency [8]. To address the issues of accurate and reliable estimation of grasping posture for complex shaped objects, Cheng H et al. designed a vision-based depth grasping detector, which uses a densely connected feature pyramid network and multiple two-stage detection units to achieve dense grasping posture, achieving accurate grasping posture detection and gripper opening measurement [9]. Jiang J et al. proposed a new framework for visually-guided tactile detection to solve the problem of robots grasping transparent objects. The segmentation network was utilized to predict the horizontal upper region on the transparent object as the detection area, which is detected by a high-resolution haptic sensor to obtain the precise contour, improving the detection accuracy and grasping success rate of the transparent object [10]. Aiming at the problem that industrial robotic arms lack high-precision visual recognition ability, Wu Y proposed a visual recognition optimization method based on neural network and Transformer model. By combining the feature extraction ability of the deep learning model and the attention mechanism, the object recognition and grasping localization accuracy of the robot could be improved, and the autonomous operation ability and adaptability of the robotic arm in industrial scenes could be enhanced [11].

In addition, for the problem of robot grasping pose estimation for complex objects in unstructured environments, Cheng H et al. proposed a novel depth model for anchorless fully convolutional grasping pose detection. The grasping pose was considered as a rotating bounding box on the image plane, and the six-channel image was directly output to represent the key points and geometric information of the grasping rectangle, which improved the accuracy and efficiency of the grasping detection [12]. Regarding the problem of robot grasping in chaotic scenes, Yu S et al. proposed a chaotic grasping network, which used a dual branch squeezing excitation residual network as the skeleton, utilized multi-scale features and refined the grasping area to improve the success rate of robot grasping in chaotic scene tasks [13]. Cao H et al. raised a novel grasping detection network to balance the accuracy and inference speed of deep learning models in general object grasping detection. The network used a grasping representation method based on Gaussian kernel to highlight the center point with the highest grasping confidence. By suppressing noise features and highlighting object features, the network improved the grasping success rate while ensuring the model running speed [14]. To solve the problem of significant object detection in robot visual perception under complex interference environment, Song K et al. raised a novel three mode image fusion strategy. By constructing an image acquisition system under variable lighting scenes, and using multi-level weighting to suppress interference, effective cross modal feature fusion was achieved, enabling the robot to quickly and accurately complete the target capture task [15]. Aiming at the problems of limited 2D grasping direction and poor real-time performance of 3D point cloud, Hui N M et al. proposed a grasping detection algorithm that fuses 2D image and 3D point cloud. An improved single-stage multi-frame detector network is used to optimize the a priori frame scaling strategy to improve the target localization accuracy, and the target spatial position is extracted by the view cone transformation and point cloud segmentation algorithms, which improves the success rate and real-time performance of the capture, and reduces the time-consumption of the capture at the same time [16]. Aiming at the problem of differentiating color, shape and size for object sorting in industrial automation, Abdullah-Al-Noman M et al. proposed a robotic arm gripping system based on computer vision. Using PixyCMU camera and OpenCV image processing technology, combined with Arduino Mega controller and servo motor drive, the system realized multi-color object recognition and geometric feature detection. The system improved the color recognition accuracy and shape classification accuracy [17].

In summary, numerous researchers worldwide have noticed the problems that exist in robot grasping detection during operation and have conducted multiple research efforts to address these issues. However, the existing models have limited perception of multi-scale targets, rely on a single attention mechanism, and have insufficient global-local feature dynamic balancing ability, which restricts accurate grasping in industrial scenarios. In addition, accurate and real-time completion of robot grasping detection is a prerequisite for expanding the scale of robot use in environments such as factory workshops, and its importance is self-evident. However, in the above studies, there have been few optimizations focused on the computational complexity of model object detection and the noise processing of grasping detection. YOLOv6 has fast inference speed, high detection accuracy, and is suitable for various embedded platforms, with flexible deployment [18]. MDAFN can suppress noise, highlight object features, enhance target perception in complex backgrounds, and improve detection accuracy [19]. Therefore, based on YOLOv6 and MDAFN, combined with lightweight network MobileViT, Pixel Shuffle (PixShuffle), etc., an L-YOLOv6-MA robot grasping detection model is established. The research fuses lightweight YOLOv6 and MobileViT to achieve parameter compression, enhances the physical-semantic association of

features through channel-pixel dual-domain attention, and balances the local grasping points and global context information by combining the multi-scale sensing field decoder, to construct an end-to-end lightweight detection framework, which effectively improves the feature expression and localization accuracy under complex interference. The research aims to provide comprehensive and innovative solutions to the accuracy and efficiency issues of robot grasping and detection in actual factories or other environments.

## III. Methods and Materials

This section is divided into two parts. The first part provides a detailed explanation of YOLOv6, Efficient Repetitive Backbone (ERB), and MobileViT, and proposes an object detection module. The second part takes MDAFN as the core, combines multi-scale receptive field Receptive Field Block (RFBs), Pixshuffle, etc., proposes a grasping detection module, and finally constructs the L-YOLOv6-MA robot grasping detection model to improve the robot grasping performance under model control.

### A. Object Detection Module Based on YOLOv6

An efficient and accurate target detection strategy is the key to achieving real-time object recognition and tracking performance in complex scenes, and it is also a prerequisite for achieving robot grasping detection performance. However, the target detection strategy of traditional robot grasping detection models usually has high computational complexity, slow response speed, and is difficult to adapt to rapid changes in dynamic environments. YOLOv6 enables efficient deployment on embedded devices, providing real-time object detection while maintaining high accuracy and low latency. Therefore, the research builds an object detection module based on YOLOv6 framework, and the basic architecture of YOLOv6 is shown in Fig. 1.

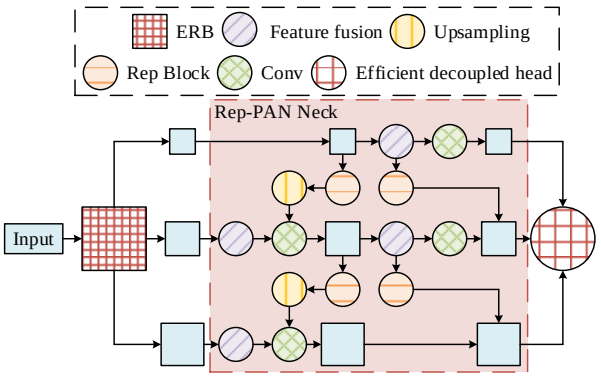



Fig. 1. The architecture of YOLOv6 networks.

In Fig. 1, the YOLOv6 backbone network adopts an ERB structure, which improves feature extraction capability and simplifies the model structure by using a simple repeated parameterized visual geometry group network structure. During training, ERB adopts a multi-branch structure to enhance performance, while during inference, it transforms into a single branch structure of Re-parameterized Block (Rep Blocks) to accelerate the prediction process [20]. The Neck section introduces a Re parameterized Path Aggregation Network (Rep-PAN) to enhance the ability of multi-scale feature fusion. The head adopts an efficient decoupling head design to separate classification and regression tasks, further improving detection accuracy and convergence speed [21]. However, when deploying YOLOv6 on small devices, there are problems such as large model size and high computational cost, which will lead to a decrease in its detection performance in low-resource environments. MobileViT combines the local feature extraction advantages of convolutional neural networks with the global information processing capabilities of visual transformers, enabling both lightweight design and efficient performance. Therefore, the study combines MobileViT for lightweight optimization of YOLOv6, and the network structure of MobileViT is shown in Fig. 2.

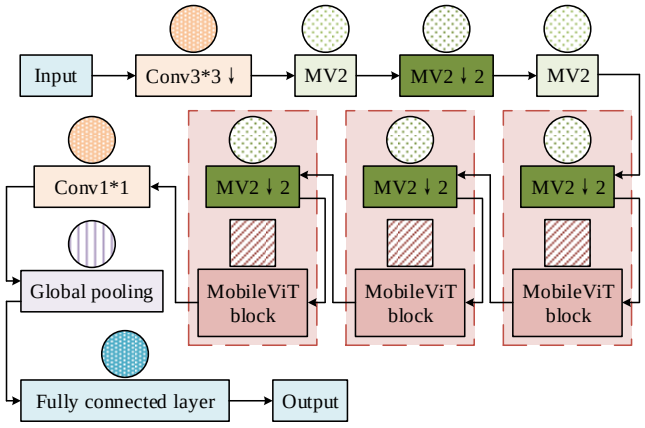



Fig. 2. The structure of MobileViT network.

As shown in Fig. 2, the MobileViT network consists of ordinary convolutional layers, MV2, and MobileViT components. The ordinary convolutional layer is responsible for preprocessing the input image and extracting low-level features. MV2 is the inverse residual structure in MobileNetV2, used for efficient downsampling operations in the network. It extracts features through 1 * 1 convolution for dimensionality enhancement and 3 * 3 deep convolution, and then compresses and expands features through 1 * 1 convolution for dimensionality reduction. The MobileViT component is the core of MobileViT, consisting of multiple Transformers, including three steps: local feature extraction, global feature modeling, and feature fusion [22]. Among them, the expansion factor of MV2 module is 6, which is responsible for controlling the proportion of channel dimensioning. Too small an expansion factor will limit the feature expression ability, while too large a factor will increase the model complexity. The number of stacked Transformer layers in MobileViT is 3, which needs to be considered as a balance between global modeling capability and computational efficiency. In addition, the global pooling layer reduces the dimensionality of the feature map to obtain global features. The fully connected layer maps these global features to the final prediction output. Therefore, the proposed object detection module architecture is shown in Fig. 3.

In Fig. 3, the input image is first subjected to feature extraction through the MobileViT network, which consists of

multiple MV2 modules. Each module is followed by a MobileViT component to downsample the feature map. The MobileViT component utilizes its lightweight design to effectively extract image features while maintaining a low number of parameters. After being processed by the MobileViT network, the feature maps enter YOLOv6 and undergo further feature fusion and processing through Simplified Spatial Pyramid Pooling-Fast (SimSPPF) and other convolutional layers and residual connections. The SimSPPF module is located in the Neck structure and replaces traditional parallel structures with serial pooling operations, reducing redundant calculations and improving the network's detection capability for targets of different sizes. The SimSPPF module is located in the Neck structure, which reduces redundant computations by replacing the traditional parallel structure with serial pooling operations. Its pooling kernel size is set to [5,9,13], where too large a kernel size blurs the small target details, while too small a kernel size does not effectively cover the large target context. The Neck structure of YOLOv6 adopts a multi-scale feature fusion strategy, which enhances the network's detection ability for targets of different sizes by horizontally connecting feature maps of different scales. Finally, the feature maps processed by Neck enter the efficient coupling head for object detection tasks.

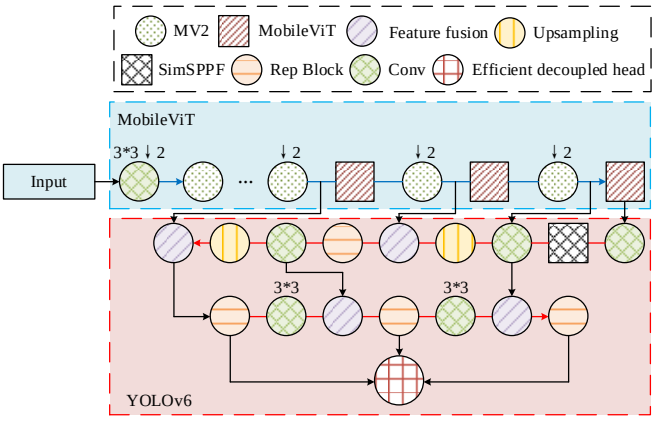



Fig. 3. The architecture of the object detection module.

## B. *Construction of Grab Detection Module and Robot Grab Detection Model*

Object detection provides visual information for robots by identifying objects in images and providing bounding boxes and categories. The proposed object detection module can achieve efficient object detection under low computing resource conditions. However, it cannot directly perform the grasping detection function. MDAFN can suppress noise features, enhance effective features, and improve the accuracy and robustness of capture detection during the fusion process of shallow and deep features. Therefore, the research focuses on MDAFN as the core and constructs a grasping detection module. The basic structure of MDAFN is denoted in Fig. 4.

In Fig. 4, MDAFN is divided into two layers: pixel attention subnetwork and channel attention subnetwork. The pixel attention subnetwork utilizes a convolutional kernel size of 3 * 3 convolutional layers. The convolutional kernel size needs to be weighed against the spatial context-awareness capability and computational overhead. A larger kernel enhances the perceptual field but increases the number of parameters. Through the convolutional layers and Sigmoid activation function, the pixel attention subnetwork assigns weights to each pixel to highlight key visual information. The channel attention subnetwork enhances important channels in the feature map through global average pooling and fully connected layers. Finally, the subnetwork weighted feature map is combined with the original input feature map to integrate pixel and channel level attention information through element wise multiplication, suppressing noise [23]. However, MDAFN has limited performance when dealing with complex backgrounds or overlapping targets, while RFB can provide richer contextual information. Therefore, research is being conducted to optimize the input of MDAFN using RFB.

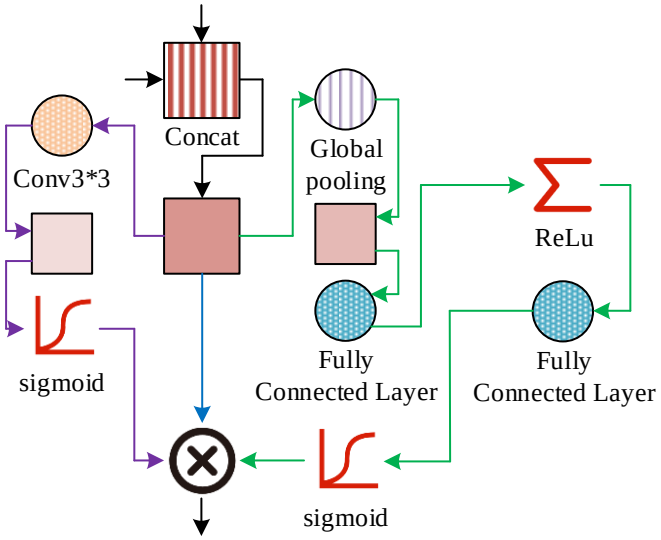



Fig. 4. The basic structure of MDAFN.

RFB aims to enhance the adaptability of the network to multi-scale characteristics by constructing convolutional layers of different scales. The operation process is as follows: RFB first adjusts the number of channels through a 1 * 1 convolution operation, and then extracts multi-scale features through convolution kernels and dilated convolutions of different scales. Its expansion rate is set to [1,3,5] and the number of multibranch channels is configured as [64,128,256], respectively. The feature maps of different scales are then merged to obtain feature representations with rich multi-scale information [24]. In addition, Pixshuffle can achieve efficient upsampling operations while preserving image details and texture information. The operation process is as follows: Pixshuffle first uses convolutional layers to increase the number of channels in the feature map to the square of the target resolution multiple. Afterwards, the channels are rearranged and each pixel's multi-channel is converted into a corresponding image block to achieve an increase in resolution [25]. Therefore, the proposed grasping detection module architecture is shown in Fig. 5.

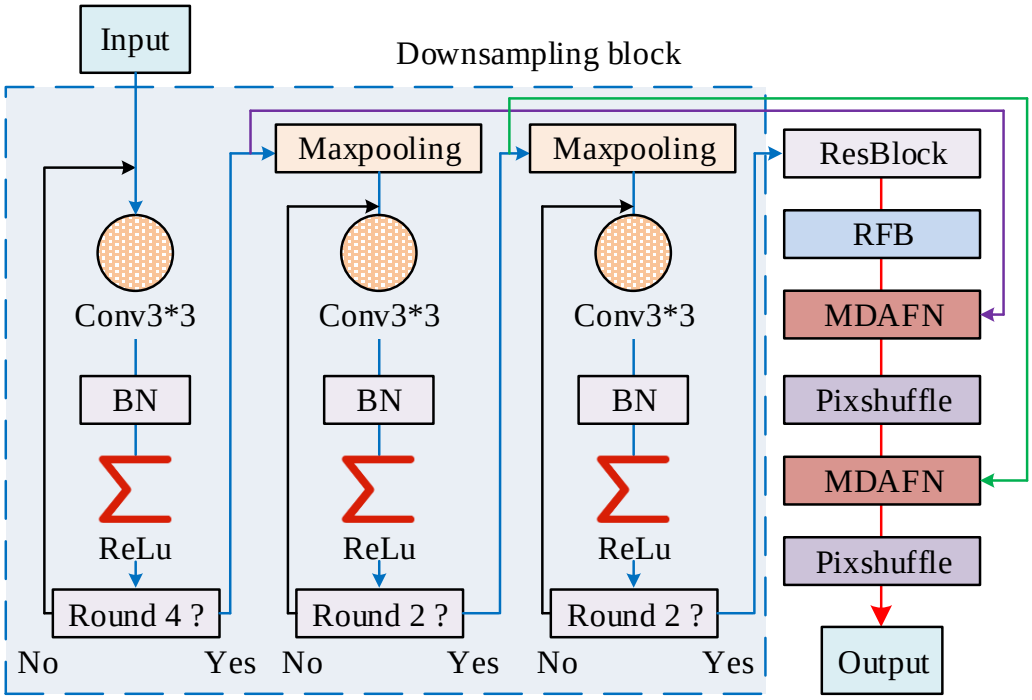



Fig. 5. The architecture of the grasp detection module.

In Fig. 5, the network mainly contains downsampling blocks and a backbone network. In the downsampling block, the input image first passes through a 3 * 3 convolutional layer, followed by a Batch Normalization (BN) layer and a ReLU activation function, and then enters a round of decision-making. If the conditions are met, it enters the max pooling layer and enters the above structure again. After three iterations, the feature outputs that meet the conditions will enter the backbone network. Residual Block (ResBlock) is the first layer of the backbone network, which works together with RFB to extract more discriminative and robust features. Afterwards, the features enter MDAFN and fuse shallow and deep semantic features. Pixshuffle serves as an upsampling layer for the capture detection module to increase feature resolution. In summary, the overall operational process of L-YOLOv6-MA, which combines the object detection module and the grasping detection module, is shown in Fig. 6.

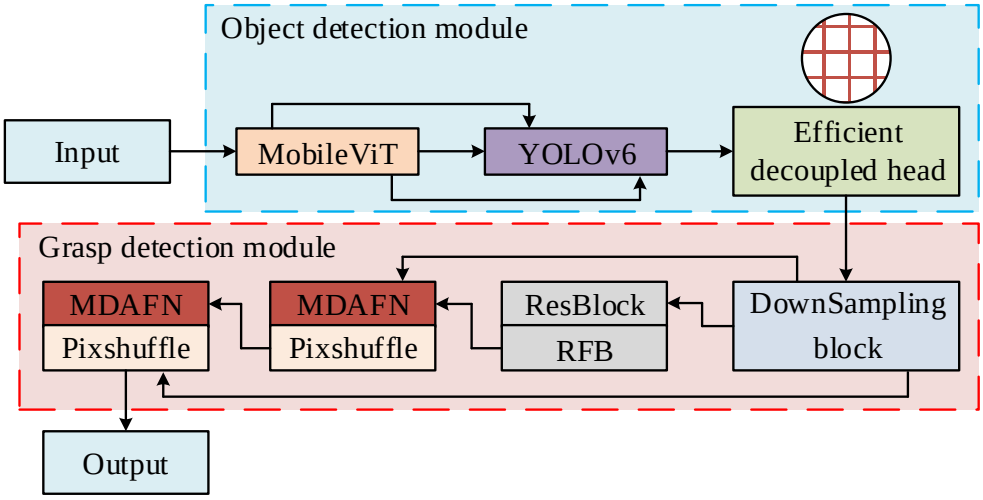



Fig. 6. The overall operation flow of L-YOLOv6-MA.

As shown in Fig. 6, the operation process of the L-YOLOv6-MA model includes two stages: object detection and grasping detection. In the object detection stage, YOLOv6 serves as the basic framework and achieves model lightweighting through MV2, MobileViT components, etc., reducing model complexity and computational costs. Fast and accurate recognition of objects in an image is achieved by convolutional operations such as SimSPPF. In the capture detection stage, MDAFN is used as the core to enhance key information in the feature map through pixel and channel

attention subnetworks, thereby improving the accuracy of capture detection. By combining structures such as RFB, Pixshuffle, and downsampling blocks, the adaptability and resolution recovery performance of the network to targets of different scales and complex backgrounds are enhanced. The model ultimately outputs the predicted grasp quality, angle and width.

## IV. Results

To prove the performance and superiority of the proposed L-YOLOv6-MA model, simulation experiments and actual model performance experiments were conducted based on the theoretical foundation and algorithm analysis mentioned above. The study analyzed the experimental results in detail and compared their performance such as detection accuracy and real-time performance.

### A. Simulation Operation Experiment

In the simulation experiment, Windows 10 was chosen as the operating system, and the NVIDIA Isaac Sim simulation platform was used to simulate the robot grasping task environment. Moreover, the study constructed a simulated robot using the Gazebo simulator and robot operating system. The study introduced Single Shot MultiBox Detector (SSD), Region Proposal Network (RPN), Hough Transform (HT), and Deep Residual Network (DRN), and compared them with the proposed L-YOLOv6-MA model, which was named L. The study first used the Microsoft Universal Object Context dataset as the object of capture detection, and conducted object detection efficiency experiments by comparing the object detection accuracy and Frames Per Second (FPS) of different algorithms. The experimental results are denoted in Fig. 7.

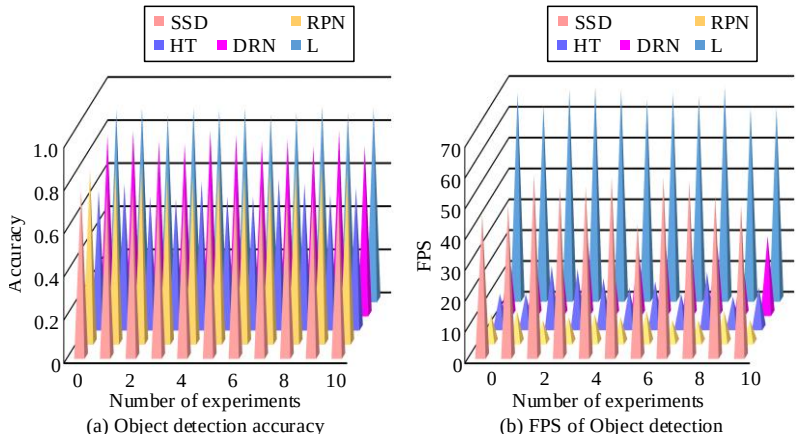



Fig. 7. Comparison of detection accuracy and FPS.

According to Fig. 7(a), the target detection accuracy of HT was the lowest, between 0.60 and 0.69. Next was SSD, with an accuracy between 0.75 and 0.78. The average accuracy of RPN and DRN was 0.80 and 0.82, respectively. The target detection accuracy of L was the highest, ranging from 0.86 to 0.90. As shown in Fig. 7(b), L also had the highest FPS, with an average FPS of 66.00. Next was SSD, with an average FPS of 52.82. The FPS ranges of HT and DRN were 10.00 to 19.00 and 20.00 to 30.00, respectively. The FPS of RPN was relatively low, with an average FPS of 8.36. The experimental findings indicated that the target detection efficiency of the proposed model was much higher than that of traditional methods. On this basis, the study explored the model's capture detection performance by comparing the image segmentation efficiency and running time of different algorithms. The experimental results are denoted in Fig. 8.

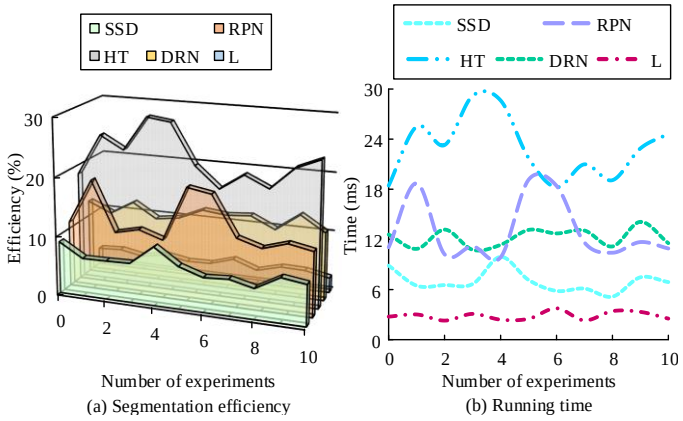



Fig. 8. Differences in segmentation efficiency and running time.

According to Fig. 8(a), the image segmentation efficiency of L was relatively high, ranging from 90.96% to 95.35%. Next was DRN, with an efficiency ranging from 82.32% to 88.41. The average efficiencies of SSD and RPN were 77.85% and 84.06%, respectively. The image segmentation efficiency of HT was the lowest, ranging from 65.09% to 73.94%. According to Fig. 8(b), HT had the longest running time, with an average time of 22.96ms. Next was RPN, with an average time of 13.01ms. The running times of SSD and DRN were between 5.14ms and 9.91ms, and 10.75m and 14.11ms, respectively. The running time of L was the shortest, with an average time of only 2.85ms. The experiment findings denoted that the image segmentation efficiency of the proposed model was far superior to other methods. Subsequently, the Receiver Operating Characteristic Curve (ROC) and Area Under the Curve (AUC) of the comparative model were studied to further investigate the performance of the model. The experiment findings are shown in Fig. 9.

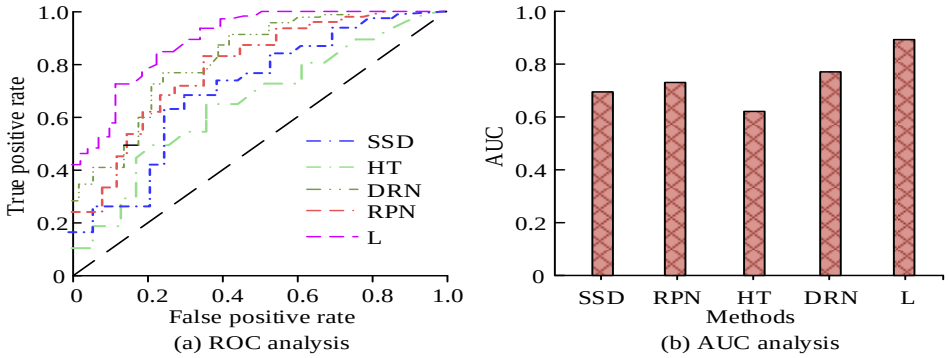



Fig. 9. Differences in ROC curves and AUC values.

As shown in Fig. 9(a), when the false positive rate (FPR) was between 0 and 0.1, the growth rate of the model's true positive rate (TPR) was the highest. Afterwards, the growth of TPR gradually slowed down and reached its maximum value after the FPR was 0.6. When the FPR was the same, the TPR of L was the highest, and the TPR of HT was the lowest. For example, when the FPR was 0.5, the TPR of L was 0.99. At this time, the TPRs of SSD, RPN, HT, and DRN were 0.79, 0.85, 0.71, and 0.89, respectively. According to Fig. 9(b), the AUC value of L was as high as 0.91. The AUC value of DRN was slightly lower, at 0.79. The AUC values of SSD and RPN were 0.70 and 0.74, respectively. The AUC value of HT was the lowest, only 0.64. The experiment findings denoted that the comprehensive effectiveness of the raised model was much higher than traditional methods.

### *B. Actual Model Performance Experiment*

Simulation running experiments are an important reference for measuring robot grasping models. However, due to the complexity and randomness of the factory environment and grasping task behavior, there are often differences between the actual performance of the model and the simulation results. Therefore, the study selected SSD and RPN as comparative algorithms for actual model performance experiments. The study selected a certain parts processing workshop as the actual experimental environment, and verified its practical promotion potential by exploring the performance of the model in the actual environment. The study first explored the actual target detection and image segmentation performance of the robot under model control for screwdrivers. The experiment results are denoted in Table I.

TABLE I. ACTUAL DETECTION AND SEGMENTATION FOR SCREWDRIVER

| Number of experiments | Detection accuracy | | | Segmentation efficiency (%) | | |
|---|---|---|---|---|---|---|
| | SSD | RPN | L | SSD | RPN | L |
| 1 | 0.69 | 0.72 | 0.76 | 75.53 | 79.71 | 85.01 |
| 2 | 0.74 | 0.74 | 0.78 | 74.75 | 74.54 | 79.32 |
| 3 | 0.74 | 0.74 | 0.76 | 72.12 | 69.09 | 84.15 |
| 4 | 0.71 | 0.75 | 0.78 | 74.49 | 73.78 | 81.62 |
| 5 | 0.70 | 0.73 | 0.75 | 70.09 | 78.15 | 78.44 |
| 6 | 0.71 | 0.73 | 0.82 | 72.71 | 73.08 | 81.43 |
| 7 | 0.69 | 0.75 | 0.83 | 70.83 | 72.22 | 80.48 |
| 8 | 0.70 | 0.76 | 0.79 | 73.61 | 74.61 | 86.45 |
| 9 | 0.73 | 0.75 | 0.82 | 68.21 | 74.69 | 80.12 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 10 | 0.73 | 0.76 | 0.82 | 75.33 | 75.25 | 83.95 |
| 11 | 0.74 | 0.73 | 0.77 | 74.89 | 77.13 | 82.03 |
| 12 | 0.75 | 0.75 | 0.83 | 68.47 | 73.75 | 80.93 |
| 13 | 0.68 | 0.77 | 0.77 | 74.46 | 71.33 | 83.35 |
| 14 | 0.69 | 0.75 | 0.79 | 72.60 | 74.77 | 82.09 |
| 15 | 0.70 | 0.72 | 0.79 | 76.50 | 75.00 | 83.80 |
| 16 | 0.69 | 0.72 | 0.83 | 74.55 | 76.88 | 80.24 |
| 17 | 0.70 | 0.74 | 0.83 | 78.81 | 75.57 | 79.17 |
| 18 | 0.69 | 0.74 | 0.81 | 72.83 | 74.07 | 83.92 |
| 19 | 0.73 | 0.71 | 0.77 | 73.69 | 75.61 | 84.82 |
| 20 | 0.75 | 0.71 | 0.75 | 72.73 | 76.74 | 85.83 |
| Mean | 0.71 | 0.74 | 0.79 | 73.36 | 74.80 | 82.36 |

According to Table I, the actual object detection accuracy of SSD was relatively low, ranging from 0.68 to 0.75, with an average accuracy of 0.71. The actual accuracy range of RPN was 0.71 to 0.77, with an average accuracy of 0.74. The actual accuracy of L was relatively high, ranging from 0.75 to 0.83, with an average accuracy of 0.79. In addition, SSD had the lowest actual image segmentation efficiency, ranging from 68.21% to 78.81%, with an average efficiency of 73.36%. The actual efficiency of RPN was 69.09% to 79.71%, with an average efficiency of 74.80%. The actual image segmentation efficiency of L ranged from 78.44% to 86.45%, with an average efficiency of 82.36%. The experiment findings denoted that the actual performance of the proposed model was much higher than traditional methods. On this basis, the grasping performance of robots controlled by comparative models on screwdrivers was studied, and the experimental results are shown in Fig. 10.

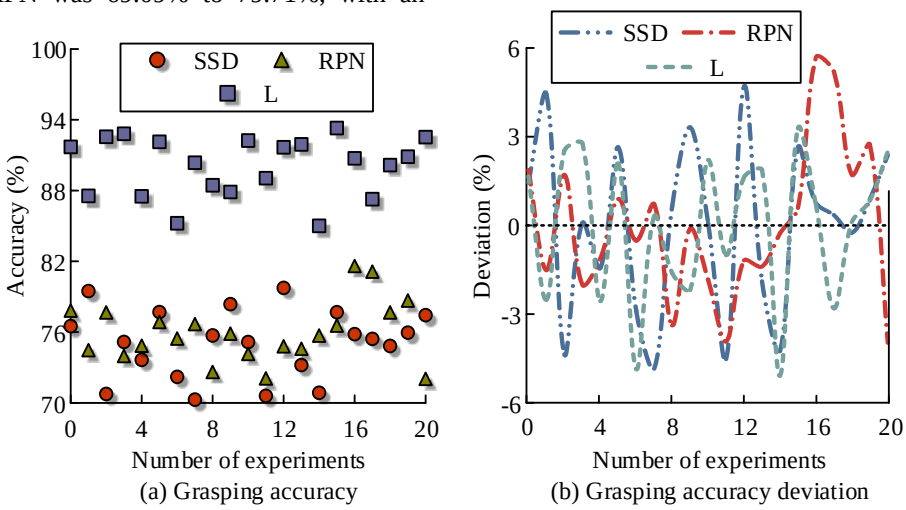
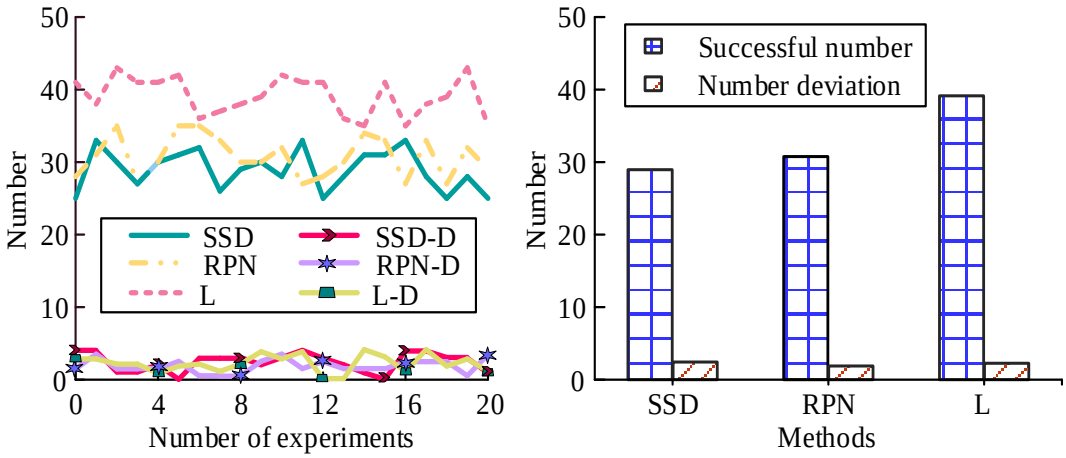



Fig. 10. Grasping accuracy and deviation for the screwdriver.

As shown in Fig. 10(a), the success rates of SSD and RPN were relatively close when controlling the robot to grab the screwdriver. The success rates of the two were divided between 70.28% and 79.75%, and 72.04% and 81.61%. At this point, the success rate range of L was 85.01% to 93.30%. According to Fig. 10(b), the success rate deviation of RPN was the smallest, ranging from -3.93% to 5.64%. Next was L, with a deviation range of -5.03% to 3.26%. The deviation of SSD was relatively large, ranging from -4.80% to 4.67%. The experiment findings denoted that under the proposed model control, the robot had the highest grasping success rate and relatively stable performance. Finally, the study designed robots controlled by different models to grasp 50 screws and explored the successful grasping times of different models. The experimental results are shown in Fig. 11.

According to Fig. 11(a), when controlling the robot to grab screws, the SSD had the lowest success rate, between 25 and 33. Next was RPN, with a success rate of 27 to 35. The success rate of L was the highest, between 35 and 43 times. According to Fig. 11(b), the absolute deviation of RPN success times was the lowest, between 0.48 and 3.52. Next was L, with an absolute deviation range of 0.14 and 4.14. The absolute deviation of SSD was the largest, ranging from 0.05 to 4.05. The experiment findings denoted that under the proposed model control, the

robot had the highest grasping efficiency and was relatively stable for smaller objects. From the above, the performance of the proposed model was much higher than traditional methods and had the potential for promotion and application.




(a) Successful number and absolute deviation (b) Average vaule

Fig. 11. Grasping number and deviation for screw.

## V. Discussion

Aiming at the problem of low performance of traditional robot grasping detection models, this study focused on YOLOv6 and MDAFN as the core, constructed object detection modules and grasping detection modules, and proposed the L-YOLOv6-MA model by combining the two. The study introduced components such as MobileViT and Pixshuffle to achieve lightweight design of the model while reducing environmental noise and improving model accuracy. The experiment findings denoted that the simulated object detection accuracy and FPS of the proposed model were between 0.86 and 0.90, and 62.00 and 69.00, respectively. The average accuracy and FPS of other methods were 0.76 and 25.00, respectively. The simulation image segmentation efficiency and running time of the model were between 90.96% and 95.35%, and 2.28ms and 3.75ms, respectively. The average efficiency and running time of other methods were 79.01% and 13.80ms, respectively. The AUC value of the model was 0.91. The average AUC value of other algorithms was 0.72. In addition, the actual object detection accuracy and image segmentation efficiency range of the proposed model were 0.75 to 0.83 and 78.44% to 86.45%, respectively. The average accuracy and efficiency of other algorithms are 0.73% and 74.08%, respectively. The gripping rate and deviation range of the screwdriver under model control were between 85.01% and 93.30%, and -5.03% and 3.26%, respectively. The average grasping rate and absolute deviation of other methods were 75.52% and 2.15%, respectively. Moreover, the successful grasping times and absolute deviation range of screws under model control were 35 to 43 and 0.14 to 4.14, respectively. The average success rate and absolute elimination of other methods were 29.86 and 2.16, respectively. In summary, the core innovations of the L-YOLOv6-MA model are: 1) establishing a synergistic architecture between YOLOv6 and MobileViT to achieve efficient feature extraction in dynamic environments through lightweight reorganization; 2) constructing a channel-pixel dual-domain attentional mechanism to strengthen the ability of grasping feature discrimination under complex background interference; 3) designing a multiscale fusion decoder that combines sense-of-field extension and subpixel localization to improve the accuracy of grasping position estimation.

## VI. Conclusion

The contribution of the L-YOLOv6-MA model is that it effectively solves the problem of grasping robustness in complex scenarios by establishing a synergistic mechanism of lightweight adaptive feature extraction and multidimensional attention. The detection framework breaks through the efficiency bottleneck of traditional staged processing, provides a high-precision and low-latency solution for shaped part grasping, and significantly improves the flexible adaptation capability and deployment efficiency of automated production lines.

While demonstrating notable advancements, this study has limitations: 1) Experimental validation primarily targets standard screw-type workpieces, requiring extended verification for reflective/flexible materials; 2) Synthetic data-based training lacks real-world physical parameter integration; 3) Hardware-specific deployment limits cross-platform adaptability, and there is insufficient coordination exists between visual detection and robotic motion control. Future work will focus on: 1) Developing multi-material grasping datasets enhanced by transfer learning to address generalization gaps; 2) Establishing a digital twin framework combining virtual simulation and physical parameters to refine predictive accuracy; 3) Creating hardware-agnostic deployment solutions for efficient edge computing adaptation across devices; 4) Implementing visual-force closed-loop coordination to enable real-time grip adjustment and slip compensation. These improvements aim to bridge the simulation-to-reality gap while optimizing dynamic control synchronization, ultimately supporting robust industrial deployment across diverse production scenarios.

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# Intellectual Property Protection in the Age of AI: From Perspective of Deep Learning Models

Jing Li*, Quanwei Huang
School of Law, Henan University of Science and Technology, Henan, China

***Abstract*—The rapid development of Artificial Intelligence (AI), especially Deep Learning (DL) technologies, has brought unprecedented challenges and opportunities for Intellectual Property (IP) protection and management. In this paper, we employ Bibliometrix and Biblioshiny to conduct a bibliometric analysis of global research at the intersection of AI-driven innovation and IP frameworks over the past decade. The findings reveal a significant annual growth rate of 15.34 per cent in publications, with an average of 5.82 citations per study, reflecting increasing academic interest. China, the United States, and India dominate the research output, but the cross-country collaboration rate is only 10.74 per cent, indicating that there is still room for improvement in global collaborative research. The current major research groups in the field, as well as different research themes, are identified through collaborative network and thematic analyses, respectively. Although the field has achieved remarkable results in technological innovation, the deep integration of legal, economic and ethical dimensions is still at an early stage. The study highlights the urgent need for interdisciplinary collaboration and enhanced international cooperation to address pressing issues such as AI-generated content (AIGC) attribution, legal applicability, and the societal impact of DL technologies in IP protection. These findings aim to support academia and industry in clarifying ownership and promoting synergistic innovation in the AI era.**

***Keywords*—*Intellectual property; Artificial Intelligence; Deep Learning; Natural Language Processing; neural network; legal applicability***

## I. Introduction

With the deepening of the digital economy and information society, the protection and management of intellectual property (IP) has become increasingly prominent. The traditional IP system is mainly constructed on the basis of the original contribution of human creators, mainly covering copyright, patent, trademark and protection measures related to original content, and its core lies in guaranteeing the exclusive right of creators to intellectual achievements [1]. However, the changes in content dissemination and the accelerated speed of information dissemination brought about by the digitalization era have made it difficult for traditional means of protection to meet the increasingly complex problems of copyright infringement, content tampering and illegal copying. Digital content protection technology has therefore emerged, and its basic goal is to protect digitized information through technical means, ensuring the integrity and authenticity of content in the process of transmission, storage and use [2].

In recent years, the rapid development of Artificial Intelligence (AI) technology has greatly promoted changes in various fields. In the context of the AI era, IP issues also reflect many new features. The emergence of AI-Generated Content (AIGC) has made the attribution of intellectual property rights such as copyrights, patents and trademarks extremely complex [3]. DL models represented by Generative Adversarial Networks (GANs), Diffusion Models, and Transformer are capable of generating highly realistic images, audio, video, and text, which not only bring new development opportunities for the cultural and creative industries, but also raises a series of legal and ethical issues, such as the identification of "creators", the attribution of copyright, and the division of responsibility [4].

In the traditional IP field, the application of DL has shown great positive effects. In patent classification and retrieval, traditional patent databases are huge and text lengthy, and there are limitations in manual classification and keyword matching methods. Natural language processing (NLP) based on DL (e.g., BERT, Siamese Network) can automatically parse patent text, perform accurate classification and semantic matching, and improve the efficiency and accuracy of patent retrieval. For example, Chen et al. [5] proposed a DL-based patent retrieval framework that leverages entity recognition and semantic relation extraction, and achieved better accuracy than traditional methods by efficiently extracting fine-grained information. In terms of digital copyright monitoring and infringement detection, using models such as convolutional neural networks (CNNs) and visual transformer (ViT), feature extraction and matching can be performed on digital media such as pictures, videos, and audios to realize automatic detection of infringement. Fang [6] proposed a copyright management system that combines deep belief network (DBN) and blockchain technology to identify and track copyright-protected music content. Lin [7] proposed a CNN-based framework for copyright protection and risk assessment in literary works. The model detects potential copyright infringements by identifying substantial overlaps and stylistic similarities with registered content. In trademark identification and infringement analysis, the DL model can automatically identify similar or counterfeit trademarks by extracting visual features, assisting in determining the risk of confusion and effectively protecting brand image. Alshowaish et al. [8] proposed a trademark similarity detection system based on VGGNet and ResNet to retrieve trademarks based on shape similarity to facilitate and improve the accuracy of the examination process.

Meanwhile, researchers are committed to solving new problems in the AI era through DL models. In terms of traceability and marking of AIGC, DL techniques help to trace the origin of generated content by embedding digital watermarks

*Corresponding Author.

or identifiers of generated content (e.g., through invisible watermarking techniques) to solve the problems of copyright attribution and prevention of misuse. Rouhani et al. [9] proposed an end-to-end IP protection framework that protects the IP rights of owners of neural network architectures by inserting coherent digital watermarks. In terms of technological innovation trend prediction, DL technology can mine global patent data and technical literature to predict future technological hotspots and innovation trends, and assist enterprises in strategic planning and decision-making. Jiang et al. [10] proposed a DL framework for predicting patent application outcome by mining and fusing the features of text content and context networks. In addition, in the context of integrated IP management, the multimodal DL model is able to identify infringements and improper uses in cross-media environments through the joint understanding of text, image and video information. Li et al. [11] constructed a multimodal large-scale dataset for strictly annotated product patent infringement detection, examined the performance of different DL models in detecting potential patent infringements, and proposed a simple and effective infringement detection process.

However, as technology continues to evolve, new technologies bring convenience and efficiency while also raising new legal risks and challenges. First, in order to train DL models, it is usually necessary to rely on a large amount of data, which may contain a large amount of copyrighted material, and the problem of unauthorized use of data exacerbates the risk of copyright infringement to a certain extent [12]. Second, the misuse of deep generative models, such as the dissemination of falsified images, videos, and false information, also poses a serious test of existing legal regulation and ethical norms. Issues such as the reversibility of digital watermarking, privacy leakage, and technology abuse have gradually emerged, exacerbating the lag of traditional IP laws and policies in responding to the impact of emerging technologies. The diversified applications of AI in the form of Sora, Midjourney and Stable Diffusion have greatly reduced the technical threshold and economic cost of knowledge production, but also blurred the boundaries between originality and imitation, posing potential infringement risks to the traditional IP protection system constructed on the basis of “human creation”. This is a potential infringement risk to the traditional intellectual property protection system based on “human creation” [13]. Finally, the “black box” nature of DL models makes the definition of responsibility blurred in the event of infringement, misjudgment or disputes, which is particularly prominent in the attribution of AIGC and infringement disputes [14]. Therefore, how to effectively avoid the potential risks of DL technology while utilizing its advantages has become an important issue in today's IP research.

Based on the above background and status quo, this study is based on bibliometric methodology and utilizes Bibliometrix and Biblioshiny tools to systematically sort out and quantitatively analyze AI-driven IP (AID-IP) research in the past decade from the perspective of DL models. First, the bibliometric study can reveal the overall structure, hot topics, and knowledge evolution trends of the research in this field, and grasp the cross-fertilization between different disciplines. Second, the bibliometric study can help identify high-impact literature, core journals, and key research groups, and clarify which DL methods have made breakthroughs in IP applications, and what technical and legal issues remain to be resolved. Finally, this study not only provides a basis for quantitative evaluation of existing research, but also provides data support for future policy formulation, improvement of regulatory mechanisms, and deepening of interdisciplinary research.

This research aims to address the following key questions:

Q1: Over the past decade, what has been the trend in the number of publications, citation patterns, and core journals in AID-IP research? Can the evolution of these themes reveal emerging IP challenges in the context of AI era?

Q2: What differences can be observed in the contributions of different countries or regions to AID-IP research, based on geographic distribution and collaboration network data? What implications do these differences have for global IP protection strategies?

Q3: In the context of the AI era, what specific areas does DL technology cover in IP applications? What are the most prominent challenges in each subfield?

Q4: Based on the thematic analysis results, is there a gap in the literature regarding the application of DL technology in IP protection and its discussion within the context of IP laws and policy frameworks? What theoretical or practical shortcomings does this gap reflect? How should future research break through existing theoretical frameworks to better address the needs of technological development and legal regulation?

These research questions not only provide a quantitative overview of technological advancements in the AID-IP domain from a bibliometric perspective but also delve into interdisciplinary intersections, theoretical gaps, and legal and policy challenges in a globalized context. Traditional literature has primarily focused on algorithmic optimization and performance validation. However, discussions on the compatibility of DL technologies with existing IP legal frameworks, the ambiguity of their boundaries, and the resulting legal risks remain insufficient. A bibliometric approach is therefore essential to capturing the broader developmental trajectory of this research domain, offering data-driven insights and theoretical foundations for future in-depth studies.

The following sections of this paper are organized as follows: Section II outlines the research methodology, including data collection procedures and the application of bibliometric tools. Section III presents the key findings, focusing on publication trends, citation patterns, geographical distribution, collaboration networks, and thematic developments within AID-IP research. Section IV provides a critical discussion of the results in relation to the research questions posed in the introduction. Finally, Section V concludes the paper by summarizing the main insights, emphasizing both theoretical and practical implications, and suggesting directions for future research.

## II. METHODS

This study employs a bibliometric approach, leveraging Bibliometrix and Biblioshiny to systematically analyze research on AID-IP protection and management over the past decade. Data is sourced from the Web of Science Core Collection (WoSCC) and Scopus.

### A. Dataset Construction

The first step in bibliometric analysis is literature identification and selection. The data collection process is illustrated in Fig. 1.

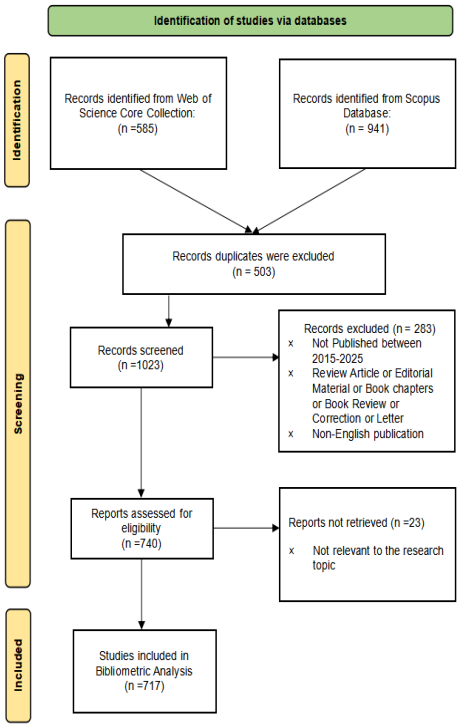


Fig. 1. Flowchart of the dataset collection process.

In this study, WoSCC and Scopus serve as the primary data sources. The search query used is as follows: TI = (("Artificial Intelligence" OR "AI" OR "Deep Learning" OR "Machine Learning" OR "Neural Network") AND ("Intellectual Property" OR "Patent" OR "Copyright" OR "Content Protection" OR "Trademark")). The search was conducted in February 2025 to capture studies at the intersection of AI technologies—including machine learning, neural networks, and generative AI—and IP filed, covering patents, copyrights, trademarks, and digital content protection.

The initial search retrieved 585 records from WoSCC and 941 from Scopus. After removing 503 duplicates, 1,023 unique records remained for further screening.

Studies published outside the 2015-2025 timeframe were excluded from the screening process to ensure that the analysis focused on the most recent advances in AID-IP research. Irrelevant document types including reviews, book chapters, corrections, and letters were excluded. Additionally, non- English publications were removed to maintain consistency in the linguistic analysis. This resulted in 740 documents for further eligibility assessment. Finally, 740 articles were assessed in full text for direct relevance to the research topic of this paper through manual review and discussion between two researchers. 23 studies that passed the initial screening but were not directly relevant to research focus were excluded at this stage. After completing a rigorous screening and eligibility assessment, 717 studies were considered highly relevant and included in the bibliometric analysis. All search results were exported to BibTeX format for standardized processing in Bibliometrix.

### B. Bibliometric Analysis Tools

After completing the construction of the dataset, key metrics and network analyses were conducted using Bibliometrix and its web-based interface Biblioshiny in R [15-16]. To assess citation impact, we use Mean Total Citations per Article (MeanTCperArt), calculated as:

$$\text{MeanTCperArt} = \frac{\text{Total Citations}}{\text{Total Articles}} \quad (1)$$

This metric indicates the average scholarly influence of the documents analyzed and supports comparative evaluations across authors, journals, or time periods.

The co-citation network was constructed using a minimum co-citation threshold of 15 to exclude weak relationships and retain frequently co-cited references. The Louvain modularity algorithm was applied to detect thematic clusters based on internal citation strength. The modularity $Q$ is defined as:

$$Q = \frac{1}{2m}\sum_{i,j}[A_{i,j} - \frac{k_i k_j}{2m}]\,\delta(c_i, c_j) \quad (2)$$

where, $A_{i,j}$ is the edge weight between nodes $i$ and $j$, $k_i$ and $k_j$ are their respective degrees, $m$ is the total number of edges, and $\delta(c_i, c_j)$ is 1 if nodes $i$ and $j$ belong to the same community and 0 otherwise. This formula evaluates how well a network is partitioned into modules with dense internal connections.

Author Keywords occurring at least ten times were used to build the keyword co-occurrence network. Nodes represent keywords, and edges indicate the frequency of co-occurrence in the same document. To assess keyword importance, we applied three centrality measures: PageRank, Betweenness Centrality and Closeness Centrality.

To examine collaboration patterns, we constructed author- level and country-level networks. The Leiden algorithm was used for community detection, offering improvements over Louvain by ensuring community connectivity and faster convergence. It can optimize various objective functions, such as modularity or the Reichardt–Bornholdt (RB) Potts model, expressed as:

$$H = -\sum_{i,j}(A_{ij} - \gamma \cdot P_{ij})\,\delta(c_i, c_j) \quad (3)$$

where, $A_{ij}$ represents the weight of the edge between nodes $i$ and $j$. $P_{ij}$ is the expected weight of the edge between $i$ and $j$ under a random model, $\gamma$ is the resolution parameter that adjusts the scale of community detection.

To normalize the collaboration strength, we used the Jaccard similarity coefficient, defined as:

$$\text{Jaccard}(A,B) = \frac{|A \cap B|}{|A \cup B|} \quad (4)$$

For both author and country-level collaborations, only edges with at least two co-authored publications were retained, and isolated nodes were excluded to focus on significant partnerships.

These multilevel and multifaceted analyses provide a clear view of the connections between different studies [16]. Finally, through thematic analysis, the main research directions and hot issues in the field are presented, and the relationship networks and knowledge maps between various themes are drawn, so as to fully grasp the research lineage and future trends.

## III. Results

Based on the constructed experimental dataset, this section uses Bibliometrix and Biblioshiny to give the results of basic statistical analysis, collaborative analysis, and thematic analysis of the relevant studies on AID-IP in the last decade, and visualization to intuitively show the complex data relationships, so as to obtain a more detailed interpretation of the academic pulse.

### A. General Analysis

Table I gives a quantitative summary of the experimental data. It can be observed that the data comes from 455 different sources including journals, books and conference proceedings, highlighting the interdisciplinary nature of AID-IP research. The annual growth rate of literature publication over the past decade was 15.34%, with an average of 5.824 citations per study, indicating a rapid increase in academic interest in AID-IP research. In addition, the average age of the literature is 3.05 years, attesting to the current activity of the field. The dataset contains 1,833 keywords plus (ID) and 1,623 author keywords (DE), reflecting diverse and rich research topics. The dataset contains 1,647 authors, with a relatively low percentage of single-author papers and an average of 3.07 co-authors per document, reflecting the collaborative and interdisciplinary nature of AID-IP. However, cross-national collaboration only accounts for 10.74 per cent, reflecting the fact that international cooperation is yet to be further improved.

Table II provides a detailed listing of annual publication metrics for the field, including total publication count (N), mean total citations per article (MeanTCperArt), mean total citations per year (MeanTCperYear), and the number of citable years. It can be observed that AID-IP research results show a continuous growth trend, with the number of publications increasing significantly over the years, from 6 articles in 2015 to 192 in 2024. The data for this study was collected from February 2025, so the 2025 data does not reflect the annual trend. MeanTCperArt and MeanTCperYear both peaked in 2018, reflecting the high impact of articles published during this period. The current low citation rate for new research in recent years should not be viewed as a lack of impact, but rather as a delayed citation effect. Overall, the publication metrics reflect a vibrant and expanding field of research that is being shaped by AI, IP, and emerging technologies.

Table III lists the top ten sources contributing the most articles in the field, demonstrating the main platforms for disseminating AID-IP research. It is evident that World Patent Information, Journal of Intellectual Property Law & Practice, and GRUR International are among the top contributors, reflecting the close intersection between AI, IP, patents, and legal frameworks. IIC-International Review of Intellectual Property and Competition Law and Journal of World Intellectual Property further indicate academic interest in the legal, economic, and policy implications of AID-IP. In addition, CEUR Workshop Proceedings, Lecture Notes in Computer Science, IEEE Access, and Lecture Notes in Networks and Systems highlight the significance of AI-driven innovations in IP protection. The top sources reflect the highly interdisciplinary nature of AID-IP research, spanning law, policy, and computer science research. In addition, the conference proceedings play an important role in highlighting the rapidly evolving nature in this area.

TABLE I. Statistical Information of the Dataset

| Description | Results |
|---|---|
| MAIN INFORMATION ABOUT DATA | |
| Timespan | 2015:2025 |
| Sources (Journals, Books, etc) | 455 |
| Documents | 717 |
| Annual Growth Rate % | 15.34 |
| Document Average Age | 3.05 |
| Average citations per doc | 5.824 |
| DOCUMENT CONTENTS | |
| Keywords Plus (ID) | 1833 |
| Author's Keywords (DE) | 1623 |
| AUTHORS | |
| Authors | 1647 |
| Authors of single-authored docs | 152 |
| AUTHORS COLLABORATION | |
| Single-authored docs | 168 |
| Co-Authors per Doc | 3.07 |
| International co-authorships % | 10.74 |
| DOCUMENT TYPES | |
| Article | 457 |
| Article; early access | 11 |
| Conference paper | 167 |
| Proceedings paper | 82 |

TABLE II. Annual Scientific Production

| Year | N | MeanTCperArt | MeanTCperYear | CitableYears |
|---|---|---|---|---|
| 2015 | 6 | 1.5 | 0.14 | 11 |
| 2016 | 6 | 4.5 | 0.45 | 10 |
| 2017 | 13 | 9.31 | 1.03 | 9 |
| 2018 | 27 | 29.11 | 3.64 | 8 |
| 2019 | 46 | 6.24 | 0.89 | 7 |
| 2020 | 79 | 11.7 | 1.95 | 6 |
| 2021 | 84 | 9.82 | 1.96 | 5 |
| 2022 | 101 | 5.76 | 1.44 | 4 |
| 2023 | 138 | 2.8 | 0.93 | 3 |
| 2024 | 192 | 1.16 | 0.58 | 2 |
| 2025 | 25 | 0.24 | 0.24 | 1 |

TABLE III. TOP 10 SOURCES

| SI. | Sources | Articles |
|---|---|---|
| 1 | World Patent Information | 20 |
| 2 | Journal of Intellectual Property Law & Practice | 18 |
| 3 | Scientometrics | 17 |
| 4 | GRUR International | 13 |
| 5 | CEUR Workshop Proceedings | 11 |
| 6 | IIC-International Review of Intellectual Property and Competition Law | 10 |
| 7 | Lecture Notes in Computer Science | 10 |
| 8 | Journal of World Intellectual Property | 9 |
| 9 | IEEE Access | 8 |
| 10 | Lecture Notes in Networks and Systems | 8 |

Fig. 2 gives the country distribution of AID-IP research over the last decade. Dark blue regions (e.g., China, USA, India) indicate active research activity. Light blue areas (e.g., South America, Africa, and parts of Europe) indicate moderate research participation. Gray areas indicate limited or no research activity in AID-IP. China and the United States occupy the top two positions with 404 and 114 articles, respectively, reflecting the high priority and continued leadership of China and the United States in AI, IP, and patent-related innovation. India ranked third with 75 articles, reflecting its growing influence in AID-IP research.

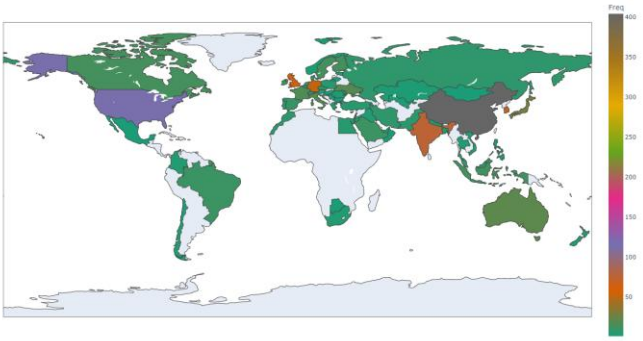

Fig. 2. Geographic distribution.

As can be seen from the results in Fig. 2, China, U.S., and India are leading the way in AID-IP research. Asian countries, particularly China, India, South Korea, and Japan, all rank high in this area, indicating a strong technical and legal focus on AI- driven innovation. Europe has several active contributing countries, including Germany, the UK, France and Italy. The UK is the largest major contributor in Europe with 61 articles, reflecting its strong focus on AI regulations and IP policies. Emerging contributors such as Saudi Arabia and Brazil highlight the growing global interest in AID-IP research.

Academic journals are important platforms for presenting scientific research results, and as the creators of scientific research content, authors affect the competitiveness and influence of journals to a large extent. Therefore, identifying core authors has also become one of the key aspects in intelligence research. Fig. 3 gives the top ten authors with the largest number of publications in AID-IP research. Among them, LIU W, ZHANG Y, and WANG J ranked the top 3 with 16, 14, and 13 articles, respectively, indicating that they have made great contributions and have influence in this field.

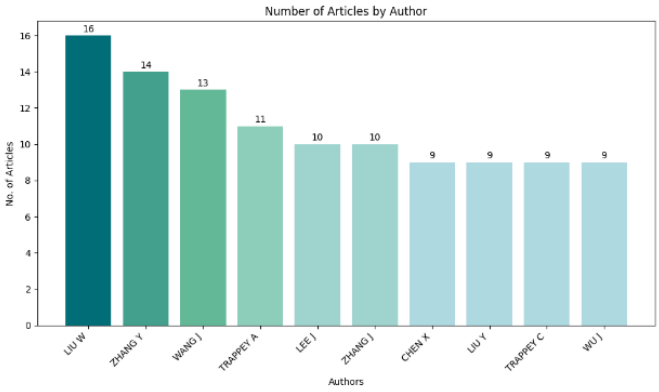


Fig. 3. Most productive authors.

Table IV lists the 10 most cited documents between 2015 and 2025. These high-impact studies not only cover a variety of aspects such as patent classification, technology trend prediction, and IP protection for deep neural networks (DNNs), but also reflect the wide application and continuous evolution of DL technology within this field. In terms of the overall trend, most of the highly cited literature is concentrated in the period from 2018 to 2021, which is closely related to the wide application of DL technology in various fields, and also indicates that IP issues have ushered in unprecedented challenges and opportunities in the era of AI.

From a DL perspective, these studies demonstrate various DL-based technical methods. For instance, Li et al. [17] applied CNN and word embedding techniques for patent classification, highlighting the efficiency of DL in information extraction and text classification. Similarly, Lee and Hsiang [18] showcased the potential of pre-trained language models, specifically BERT, in processing patent literature. Furthermore, concerning the IP protection of DL models themselves, Zhang et al. [19] emphasized the importance of DNN watermarking technology in safeguarding model intellectual property, while Li et al. [20] further validated the role of blind watermark frameworks in proving model ownership. Other studies, such as Cao et al. [21], explored the use of classification boundary fingerprints, which leverage DL's non-linear features and high-dimensional representations to support model protection.

Further analysis reveals that there are not only innovations at the technological level, but some studies also attempt to integrate law, policy and technology. For example, Levendowski [22] explored the role of copyright law in remedying the problem of potential bias in AI, suggesting that the interdisciplinary integration of DL technology and legal regulation in the process of IP protection is becoming an important direction for future research. Meanwhile, Lee et al. [23] showed how multiple patent indicators and machine learning methods can be used to identify emerging technologies in advance, which is important for judging technology trends and guiding industrial decisions.

TABLE IV. TOP 10 MOST CITED ARTICLES

| SI. | Title | Citations | Year | Authors |
|---|---|---|---|---|
| 1 | Protecting intellectual property of deep neural networks with watermarking | 218 | 2018 | Zhang et al. |
| 2 | Early identification of emerging technologies: a machine learning approach using multiple patent indicators | 136 | 2018 | Lee et al. |
| 3 | Forecasting artificial intelligence on online customer assistance: evidence from chatbot patents analysis | 121 | 2020 | Pantano & Pizzi |
| 4 | DeepPatent: patent classification with convolutional neural networks and word embedding | 94 | 2018 | Li et al. |
| 5 | Trends and priority shifts in artificial intelligence technology invention: a global patent analysis | 86 | 2018 | Fujii & Managi |
| 6 | How to prove your model belongs to you: a blind-watermark based framework to protect intellectual property of DNN | 78 | 2019 | Li et al. |
| 7 | Patent classification by fine-tuning BERT language model | 73 | 2020 | Lee & Hsiang |
| 8 | IPGuard: protecting intellectual property of deep neural networks via fingerprinting the classification boundary | 61 | 2021 | Cao et al. |
| 9 | How copyright law can fix artificial intelligence's implicit bias problem | 57 | 2018 | LEVENDOWSKI |
| 10 | Using supervised machine learning for large-scale classification in management research: the case for identifying artificial intelligence patents | 52 | 2023 | Miric et al. |

In addition, the temporal distribution and citations of the literature reflect the trend of DL's continuous maturation and proliferation within the IP domain. Early work focused on DL modeling for IP protection, and over time, the research scope has gradually expanded to intelligent classification of patent texts and prediction of technological frontiers, suggesting that researchers are utilizing DL modeling to mine more detailed and multifaceted knowledge information. This trend not only helps to understand the current pulse of technological development, but also lays the foundation for future cross-disciplinary cooperation and exploration of new methods.

### B. Network Analysis

Network analysis is a key method in bibliometric research, widely used in the fields of author collaboration networks, national collaboration networks and co-citation networks. Through visualization and quantitative analysis methods, it provides a powerful tool for understanding the complex relationships of scientific research activities and helps to gain insight into the patterns of scholarly communication.

The author collaboration network identifies the core authors, key collaboration groups, and the organizational structure of the research team by analyzing the collaborative relationships among researchers, which provides a basis for the impact assessment and team building of researchers. The author collaboration network of the experimental dataset is shown in Fig. 4. The visualization was generated using the Leiden clustering algorithm, with Jaccard normalization applied to the network data. In the figure different colors are used to distinguish different research groups. The node size is related to the importance of the author in the collaborative network. The connecting line indicates the collaboration between nodes, the thicker the connecting line, the more collaboration between these two authors.

The results reveal that the red cluster is led by Zhang Y, Liu W, and Wang J, represented by larger red nodes and stronger connecting edges. This group focuses on utilizing DL technologies (particularly the features of DNNs) to design embedded watermarking and anti-counterfeiting techniques to ensure model ownership and tamper-proof capabilities [19]. The cluster is concerned with embedding unique identifiers into models, thus providing verifiable evidence in cases of model theft or infringement. This practical approach offers tangible IP protection for the increasingly commercialized AI models, serving as a crucial safeguard for the commercialization of AI products.

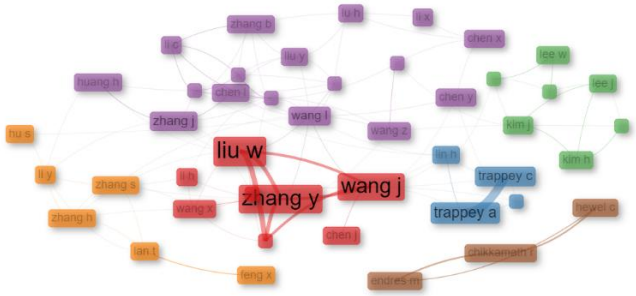


Fig. 4. Collaboration network - Co-authorship between authors.

The purple cluster includes authors like Chen L, Zhang J, and Huang H, who combine DL technologies with traditional IP protection legal frameworks. They explore how data-driven technologies can improve patent classification or technology trend forecasting, while also providing insights for revising legal provisions [24].

The key members of the green cluster include Lee W, Kim J, and Chen Y, who apply advanced DL methods for intelligent processing and trend forecasting of patent data. This cluster provides forward-looking management tools and decision- making support for IP issues within the rapidly changing AI technology field [18], [23].

The blue cluster is led by Trappey C and Trappey A, with a focus on revealing global trends, regional distribution, and industry evolution in AI technology and IP development through big data and patent network analysis. The cluster emphasizes cross-regional strategy and policy discussions [25].

The brown cluster includes authors like Hewel C, Chikkamath R, and Endres-M, who focus on IP issues in specific application scenarios. They examine practical case studies of model, patent, or copyright protection in the commercialization

process [26]. This cluster primarily explores innovative applications beyond traditional analytical frameworks, focusing on edge applications and complementary methods.

The national cooperation network can reveal the research cooperation relationship between different countries and explore the global distribution of research resources. The national cooperation network of the experimental dataset is shown in Fig. 5, in which the darker the color, the more research results, and the thicker the line, the closer the cooperation relationship. It can be found that the network presents a hub-and-spoke structure, with China and the United States serving as the central hubs to promote cooperation with multiple countries. Europe forms a dense sub-network characterized by strong intra- regional research partnerships. Emerging AI research countries (e.g., India, Australia, and South Korea), on the other hand, are increasingly integrated into the global network.

Fig. 5. Collaboration network - Co-authorship between countries.

However, there are obvious clusters and imbalances in academic cooperation and exchanges between different countries or regions. Many developing countries or regions have difficulty in participating deeply in global cooperation networks due to the relative lack of research funding, infrastructure and human resources; even if a few researchers are involved in international projects, they are often in a relatively marginalized position. This imbalance is illustrated in the figure by the sparse or almost empty "connecting lines" in some regions. Some marginalized countries are less integrated in global networks. Cooperation between Latin America, Africa and South-East Asia needs to be further strengthened in order to further increase global research equity.

The co-citation network identifies influential classic literature, theoretical foundations, and core research areas by analyzing co-citation relationships between literature. Fig. 6 gives the co-citation network results for the experimental dataset. It can be found that the yellow cluster focuses on the development of DL architectures (CNN, GAN, etc.) and AI innovations [27-30]. The Green cluster focuses on the application of AI in patent analysis, technology forecasting and IP research [31-33]. The blue cluster focuses on legal aspects of AID-IP and policy discussions [34-35]. The red cluster, on the other hand, looks at patent analysis, innovation management and the economic impact of patents [36-37]. From the results in the figure, it can be observed that the yellow and green clusters are closely connected, indicating a strong link between DL technological advances and their application in patent analysis. The blue cluster is relatively independent, suggesting that the legal discussion around AID-IP forms a distinct research area.

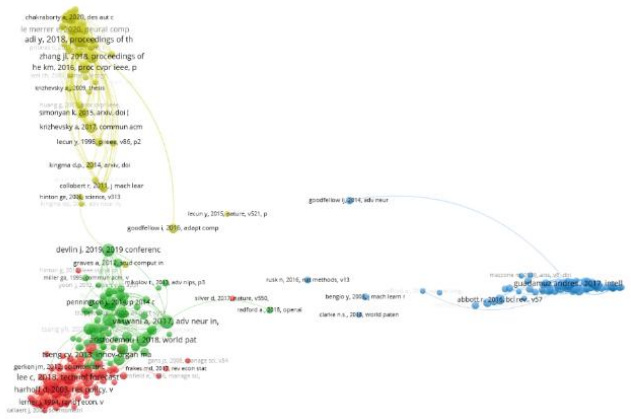

Fig. 6. Co-citation network.

## C. Thematic Analysis

Fig. 7 gives the results of the word cloud visualization, visualizing the most common terms associated with AID-IP research. The size and coarseness of each term indicates its prominence in the research literature. It can be noticed that 'Artificial Intelligence' is the main keyword, and 'Machine Learning' and 'Deep Learning' occupy a prominent position, reflecting the key role of these technologies in AI research. 'Copyright', 'Copyright Law' and 'Copyright Protection' highlight the role of AI in copyright management, originality detection, and plagiarism detection. 'Natural Language Processing' emphasizes the impact of AI on text processing, information retrieval, and legal document analysis. 'Generative AI' demonstrates the growing concern about ownership, authorship, and copyright enforcement of works generated by AI.


Fig. 7. Word cloud.

In addition, "Blockchain", "Data Mining", "BERT", and "Transformer" appear in the word cloud, revealing the growing intersection between advanced AI technologies and IP protection. "Patent Classification" and "Patent Protection" shows that AI is being widely used to automate patent analysis, detect infringement, and improve the efficiency of patent searches.

Word clouds exemplify different intersections between DL and IP. The first is the role of AI in IP management, including DL model-driven patent classification, infringement detection, and copyright management, as well as automated systems for analyzing large-scale patent and legal documents. Second, embodying AIGC's legal and ethical challenges focuses on copyright issues, including how AI impacts innovation, creativity, and plagiarism detection. Finally, the word cloud also reflects emerging technologies for IP protection, such as NLP

tools for contract analysis and legal text processing, and blockchain technology for ensuring IP transparency and security.

Principal Component Analysis (PCA) is used to reduce the dimensionality of the dataset while retaining the most important variance in the data [38]. The graph plots keywords in AID-IP research based on their similarity and co-occurrence patterns, with different clusters representing different topic areas.

The PCA diagram given in Fig. 8 reveals the different research themes in the field that are independent but interrelated, centered on AI and legal frameworks. The red cluster ("Artificial Intelligence," "patents and inventions," "copyright law,") represents research on AI-driven patent analysis, copyright protection, and legal aspects of AIGC. This cluster has far- reaching implications for policy development, legal revisions, and business models, and thus tends to be at the center of citations and discussions. The green cluster ("Natural Language Processing," "BERT," "patent classifications," "plagiarism detection,") focuses on research on NLP applications in patent classification, plagiarism detection, and document retrieval. Due to the mature application of NLP in patent text analysis, it has been recognized by academia and industry earlier, and the related results are more concentrated. The blue cluster ("watermarking," "intellectual property protection," "privacy protection,") focuses on cyber security, AI privacy and copyright infringement protection. The purple cluster ("convolutional neural networks," "patent infringements,") represents DL methods used in patent analysis, infringement detection, and automation. The orange cluster ("neural network models", "protection methods"), on the other hand, focuses on the use of DL to protect AI models and intellectual property. The research in the last three clusters is biased toward more specific technology implementations and application scenarios.

The five clusters in the figure are centered on legal frameworks and AI technologies, with discussions at the macro legal and policy levels (e.g. copyright, patent law, infringement issues, etc.), as well as research at the micro technology implementation level (e.g. NLP, CNN, watermarking technology, model protection, etc.). This phenomenon reflects that in the intersection of DL and IP, "legal compliance" and "technological innovation" have always been two parallel and intertwined threads. However, despite the multiple themes of "law", "AI algorithms" and "patent analysis" shown in the figure, the real interdisciplinary integration has yet to be further deepened. At present, most of the literature still remains in the static comparison or general discussion of laws and regulations and AI technology, and there is a relative lack of empirical research on specific judicial practices and business operation models. In addition, IP protection also involves economic incentives, ethical norms and social impacts, and related studies have not formed independent clusters in this figure, indicating that the multidimensional crossover in this field still needs to be expanded [39]. From the keywords of each cluster in the figure, it can be seen that the research mostly focuses on the level of technical prototypes (watermarking, model protection) or legal theories (copyright law, patent law), and there is a relative lack of discussion on the practical effects and policy evaluation, such as the case study of AIGC in judicial practice, and the criteria for the adoption of AI evidence in patent litigation.

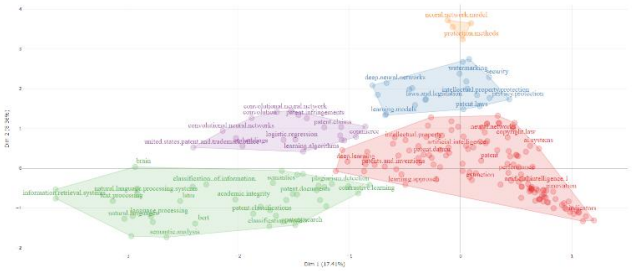

Fig. 8. Principal component analysis.

## IV. Discussion

This section will address the research questions posed in the introduction based on the bibliometric analysis results of the experimental dataset.

Q1: Over the past decade, what has been the trend in the number of publications, citation patterns, and core journals in AID-IP research? Can the evolution of these themes reveal emerging IP challenges in the context of AI era?

AID-IP research has shown a significant growth trend over the past decade, with the number of documents increasing from 6 articles in 2015 to 192 in 2024, with an annual growth rate of 15.34 per cent. The citation trend shows that 2018 is the peak year of high citations, indicating that the research in this period has had a profound impact on subsequent work, such as the application of DL in patent classification and IP protection. Meanwhile, core journals such as World Patent Information and Journal of Intellectual Property Law & Practice have become important dissemination platforms in the field, reflecting the distinctive characteristics of interdisciplinary research.

The thematic evolution path shows that the research hotspots have gradually expanded from the early focus on IP protection of DL models (e.g. watermarking technology) to intelligent classification of patented text, technology prediction, and legal challenges of AIGC. This evolution reveals emerging IP challenges arising from the rapid development of AI technologies. AIGC has been increasingly discussed in recent studies, but its legal framework is not yet mature [40]. For example, research on DNN watermarking technology provides technical security for model attribution rights, but still needs to deal with the diversity and complexity of model misappropriation [41]. DL significantly improves the efficiency of patent categorization and trend prediction, but it also raises the issue of the patent system's adaptability to technological changes. Overall, the shifting theme of the literature suggests that technological innovation is driving the upgrading of protection tools, but it also reveals the lagging problem of existing IP laws and regulatory mechanisms. Despite the gradual shift of research hotspots to emerging issues, there are still fewer studies on the adaptation of AIGC and patent legal frameworks, especially the lack of empirical studies on the impact on judicial practice.

Q2: What differences can be observed in the contributions of different countries or regions to AID-IP research, based on geographic distribution and collaboration network data? What

implications do these differences have for global IP protection strategies?

Bibliometric data shows that China and the United States dominate AID-IP research, reflecting their technological superiority and high priority in the field of AI. India comes third as an emerging contributor. European countries (e.g. Germany, UK, France) form a close regional cooperation network, while many developing countries (e.g. Latin America, parts of Africa) are less involved, and the research activities show a clear imbalance. Among the cooperative networks, China and the United States, as the central hubs of the global network, maintain close cooperation with several countries. Europe has close intra-regional collaboration but relatively little cross-regional collaboration. Emerging AI research countries such as India and South Korea are gradually integrating into the global collaborative network, but their research impact is still predominantly regional.

The dominance of China and the United States reflects their leadership in AI research investment, technology accumulation and resource reserves. Europe's close cooperation benefits from a unified IP framework and policy collaboration. However, international research and cooperation also highlights the marginalization of developing countries in AID-IP research. The regional concentration of research activities reflects global imbalances in resource allocation, talent pool and technology base. While regional cooperation can promote standardization in local areas, in the context of globalization, it is difficult to directly translate the technical or policy advantages of a single region into a global consensus. In the future, there is a need to strengthen cross-regional cooperation, especially to support the integration of developing countries into global research networks and to narrow the gap between technical and legal capabilities. With the global proliferation of AI technology, more uniform and inclusive IP protection rules need to be established at the international level. On the basis of respecting the legal and technological differences among countries, regional cooperation should be promoted to transform into globalization.

Q3: In the context of the AI era, what specific areas does DL technology cover in IP applications? What are the most prominent challenges in each subfield?

DL technology in the IP field primarily covers subfields such as digital copyright protection [42], patent classification and retrieval [43], trademark and brand evaluation [44], and technological innovation forecasting [45]. Table V lists key applications in each subfield, the commonly used DL models, and the main challenges currently faced in each area.

Currently, although DL technology has covered a number of IP application areas, the depth of research on specific areas varies, especially the empirical research related to AIGC and patent infringement is relatively small. Some of the hotspots (e.g., model protection technology) are more maturely researched, but no systematic solution has been developed for emerging issues (e.g., legal attribution of AIGC). The rapid development of DL technology has exceeded the adaptability of the existing legal framework, and the research needs to establish a closer linkage between the technology and the law.

TABLE V. KEY CHALLENGES AND COMMON MODELS FOR DL-BASED IP APPLICATIONS

| IP Field | Key Challenges | DL Models | Key Applications |
|---|---|---|---|
| Patent Classification and Retrieval | - Complex text classification<br>- Cross-lingual search | BERT, Siamese Network, FAISS | - Automatic classification<br>- Intelligent retrieval<br>- Patent trend analysis |
| Digital Copyright Protection | - Difficulty in infringement detection<br>- Tracing AIGC | CNN, ViT, GAN, CLIP | - Infringement detection<br>- DeepFake recognition<br>- Digital watermarking |
| Trademark and Brand Evaluation | - Identifying similar trademarks<br>- Detecting forgeries | ResNet, GAN, DETR | - Trademark similarity detection<br>- Counterfeit identification |
| Technology Innovation Forecasting | - Challenges in predicting future trends | LSTM, CNN, XGBoost | - Patent valuation<br>- Technology trend forecasting |

Q4: Based on the thematic analysis results, is there a gap in the literature regarding the application of DL technology in IP protection and its discussion within the context of IP laws and policy frameworks? What theoretical or practical shortcomings does this gap reflect? How should future research break through existing theoretical frameworks to better address the needs of technological development and legal regulation?

The thematic analysis shows that the literature mainly focuses on the application of DL technology itself (e.g. watermarking technology, patent classification, infringement detection), while there is less discussion of IP legal and policy frameworks. A certain degree of short layer does exist between the two. Firstly, there is a disconnect between technology and law; research on DL technology mostly stays at the level of theory and methodology, while there is less research on its legal applicability and judicial practice. Secondly, there is a lag between policy and application; issues such as attribution of AIGC products and infringement determination have become hotspots, but the adjustment and adaptation of relevant laws and policies have not yet kept pace with the development of the technology. Finally, interdisciplinary integration is still insufficient. In the past, the discussion of technical issues and legal frameworks in research was mostly independent research, lacking interdisciplinary integration in practical application scenarios.

This disconnection reflects the singular technological orientation of current research, which makes it difficult for the academic community to comprehensively assess the social costs and legal liability risks that may arise from the diffusion of the technology. Merely pursuing technological innovation while neglecting the legal, ethical and regulatory research that goes with it may lead to unforeseen problems in practical application, ultimately affecting the sustainable development of the technology. In the future, it is necessary to strengthen the integration of technology and law from both theoretical and

practical dimensions to promote the practical application of DL technology in IP protection.

Future research should start from both macro (legal framework and policy coordination) and micro (technology realization and practical application) levels. Firstly, through technological innovation, explore more efficient DL model protection techniques, such as traceability mechanisms combined with blockchain or more secure model encryption methods. Second, study the applicability of DL technology in different judicial systems and promote the coordination and harmonization of transnational legal frameworks. In terms of interdisciplinary cooperation, it should strengthen the in-depth integration of law, policy and technology fields, and promote empirical research and case analysis. Finally, it should also focus on the social impact of DL technology in IP protection, especially on industrial innovation, personal privacy and legal fairness.

## V. Conclusion

This study systematically analyzes the current research status and development trend of AID-IP field over the past decade. From the overall perspective of bibliometrics, AID-IP research has shown significant growth in the past decade, with the number of documents, citation trends and core journal distribution reflecting a high degree of academic interest in this field. The analysis of thematic evolution shows a gradual transition from single technology optimization to research at the intersection of technology and law and policy, but there is still a clear disconnect in interdisciplinary collaboration, theoretical integration and policy response. Differences in geographic distribution and international cooperation further reveal the uneven investment in technology and application in different regions, suggesting that global IP protection strategies urgently need to be more coordinated in terms of standard-setting and transnational regulation. In addition, compared with traditional methods, DL-based IP protection technologies have obvious advantages in terms of robustness and automation level, but systematic discussions on their potential risks and legal gray areas are still insufficient, and innovative research integrating technological and legal issues has not yet gained sufficient attention, which should further promote the organic integration of technological innovation and legal regulation in the future through cross-disciplinary cooperation and the establishment of new theoretical frameworks. Despite the contributions of this study, certain limitations should be acknowledged. The bibliometric analysis is based solely on data from two major academic databases—Scopus and WoSCC—which may not fully capture the breadth and diversity of research outputs in this domain. Future studies could expand the scope by incorporating additional data sources to provide a more comprehensive and inclusive understanding of the AID-IP research landscape.

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# Photovoltaic Fault Detection in Remote Areas Using Fuzzy-Based Multiple Linear Regression (FMLR)

Feby Ardianto[1], Ermatita Ermatita[2]*, Armin Sofijan[3]
Doctoral Program in Engineering Science, Universitas Sriwijaya, Palembang, Indonesia[1]
Faculty of Computer Science, Universitas Sriwijaya, Palembang, Indonesia[2]
Faculty of Engineering, Universitas Sriwijaya, Palembang, Indonesia[3]

***Abstract*—This research focused on developing and implementing a fault detection model for photovoltaic (PV) systems in remote areas, utilizing a Fuzzy-Based Multiple Linear Regression (FMLR) approach. The study aimed to address the challenges of monitoring PV systems in locations with limited access to conventional power grids and technical resources. The fault detection system integrated environmental parameters such as solar radiation, temperature, wind speed, and rainfall, alongside PV system parameters like panel voltage, current, battery voltage, and inverter performance. Data collection and preprocessing were conducted over a specified period to identify operational patterns under both normal and faulty conditions, ensuring data accuracy through cleaning, normalization, and categorization. The research was conducted in *Pandan Arang* Village, *Kandis* District, *Ogan Ilir* Regency, South Sumatera, Indonesia, contributing to the improvement of reliability and sustainability of renewable energy sources in isolated communities. The total number of data points for 276 rows with 6 attributes each was 1656 records. The MLR model was developed to predict the output power of the PV system, while fuzzy logic was employed to handle uncertainties in the data, offering a more flexible and adaptive decision-making process. The system applied fuzzy rules to determine the charging status (P3), categorizing it into Optimal Charging, Adjusted Charging, Charging Delay, or Fault Alert. The model was tested with real-time data, and its performance was validated through comparison with manual inspections. The results showed that the FMLR-based fault detection system effectively identified faults and optimized the performance of the PV system, making it suitable for remote areas in South Sumatera.**

***Keywords*—Photovoltaic; multiple linear regression; fuzzy; fault detection; remote areas**

## I. Introduction

Solar energy has become one of the most promising renewable energy sources in addressing global challenges related to energy security and environmental sustainability [1]–[3]. Photovoltaic (PV) systems have been widely implemented, particularly in remote areas where access to conventional power grids is limited. However, the effectiveness of PV systems heavily depends on the performance of solar panels, which can be influenced by various factors, including environmental conditions, dirt accumulation, shading, and component failures [4]–[6].

Fault detection in photovoltaic systems remains a major challenge in ensuring system efficiency and reliability. Undetected or delayed fault identification can lead to reduced energy production, extensive component damage, and increased maintenance costs [7], [8]. Therefore, an efficient and accurate method is required to detect faults in PV systems in real-time, especially in remote areas where technical resources and maintenance capabilities are limited [9]–[12].

The latest research trends focus on improving detection accuracy and enhancing PV system monitoring by integrating multiple data sources, including electrical performance indicators, environmental conditions, and system degradation metrics. Several key studies have significantly contributed to the advancement of fault detection g in photovoltaic (PV) arrays. Jordan & Hansen (2023) introduced a clear-sky detection approach using time-averaged plane-of-array irradiance to assess PV system health under clear-sky conditions, allowing for better identification of environmental factors affecting PV degradation using linear regression [13].

Jufri et al. (2019) developed a hybrid detection model combining regression analysis and Support Vector Machines (SVM) to detect abnormal conditions in PV systems. Their method enhanced fault prediction accuracy by incorporating daylight time and interaction variables between independent parameters, validated through multi-stage k-fold cross-validation [14]. Heinrich et al. (2020) explored machine learning techniques, particularly Logistic Regression, to monitor cleaning interventions in PV modules, ensuring optimized maintenance scheduling [15].

Harrou et al. (2021) utilized Gaussian Process Regression (GPR) and Support Vector Regression (SVR) for fault data modelling, showcasing the flexibility and adaptability of kernel-based learning methods for real-time PV system monitoring [16]. Additionally, Kim et al. (2020) introduced multivariate analysis using least-square regression to detect PV system faults, integrating both electrical and environmental parameters to provide a structured statistical framework for system health assessment [17]. These studies demonstrate the evolution of fault detection methodologies, emphasizing the role of statistical, machine learning, and hybrid approaches in improving PV system reliability and efficiency.

While previous studies primarily focused on machine learning and statistical regression techniques, a hybrid solution that integrates the strengths of fuzzy logic and multiple linear regression can be used for uncertainties decision [18]–[20]. This method is particularly advantageous in handling uncertainties in photovoltaic (PV) system operations in environmental conditions that vary significantly [21]–[23]. By

*Corresponding Author

effectively modeling nonlinear relationships between multiple independent variables—such as temperature, solar irradiance, wind speed, humidity, and power output—and their influence on fault indicators, this approach enhances the accuracy of fault detection.

Unlike traditional regression models that depend on fixed threshold values, Fuzzy-Based Multiple Linear Regression (FMLR) utilizes fuzzy membership functions to dynamically categorize data, allowing for greater flexibility in identifying faults within PV systems in South Sumatera's diverse climatic conditions [24]–[26]. Moreover, this method improves fault classification by facilitating gradual transitions between fault states rather than the rigid categorizations typically employed in Support Vector Machines (SVM) and Logistic Regression, ensuring a more adaptive and resilient monitoring system for PV operations in the region [27]–[29].

The remainder of this paper is organized as follows: Section II provides a detailed literature review on the various fault detection methods used in PV system, with a particular focus on the integration of fuzzy logic and MLR. Section III outlines the research methodology, including data collection, preprocessing, and the design of the fault detection model. Section IV presents the experimental setup and the implementation of the photovoltaic system in the remote area. Section V discuss the results and validation of the proposed model, including comparisons with manual inspection data. Finally, Section VI concludes the paper by summarizing the findings and offering recommendations for future work in PV system fault detection.

## II. Literature Review

### A. Multiple Linear Regression

Regression analysis is a statistical-based method used to analyze the relationship between independent variables (X) and a dependent variable (Y). In the context of fault detection in photovoltaic systems, Multiple Linear Regression (MLR) is often employed to assess the impact of multiple independent variables on system performance. The general equation is expressed as Eq. (1).

$$y = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n \quad (1)$$

In the context of fault detection in photovoltaic systems, the dependent variable (Y) represents the system's output or fault indicator, while the independent variables ($X_1$, $X_2$... $X_n$) include factors such as panel temperature, solar radiation, wind speed, and other operational parameters. The equation incorporates $b_0$ as the intercept (constant term) and $b_1$, $b_2$... $b_n$ as the regression coefficients, which indicate the relation to each independent variable on the dependent variable.

### B. Fuzzy Logic

In photovoltaic fault detection, once all propositions have been evaluated, the output consists of a fuzzy set that represented the contribution of each rule to the final decision that is represented and expressed as Eq. (2).

$$\mu(x_i) = (\mu_{sf}(x_i), \mu_{kf}(x_i)) \quad (2)$$

Value of $\mu_{sf}(x_i)$ denoted the membership value of the fuzzy solution up to the *i-th* rule, indicating how well a specific condition aligns with the defined fuzzy rules for system performance evaluation. Meanwhile, $\mu_{kf}(x_i)$ denoted the membership value of the fuzzy consequent up to the *i-th* rule, reflecting the degree to which the system's response or output is influenced by a given rule.

The input for the defuzzification process in photovoltaic fault detection is a fuzzy set derived from the composition of fuzzy rules, while the output is a crisp numerical value that provides a definitive assessment of the photovoltaic system's performance. Given a fuzzy set within a specific range, a crisp output can be determined using a defuzzification method. When multiple rules contribute to the decision-making process, defuzzification is performed by calculating the centre of gravity (centroid method) to determine the most representative output value. This approach helps in accurately detecting faults in photovoltaic panels, inverters, and power output variations by translating fuzzy logic-based rule evaluations into precise system diagnostics. The final crisp decision can be obtained using centroid-based defuzzification, allowing for proactive fault identification and optimization of photovoltaic energy generation as presented in Eq. (3).

$$C = max(a, b) \quad (3)$$

where, C represents the most significant fuzzy membership value, aiding in the identification and classification of faults in photovoltaic operations.

## III. Research Methdology

The research is initiated with a literature review and problem identification, which examined previous studies on fault detection in photovoltaic (PV) systems using artificial intelligence methods such as Fuzzy Logic and Multiple Linear Regression (MLR). This phase identified key challenges encountered by PV systems in remote areas and fault detection is depicted in Fig. 1.

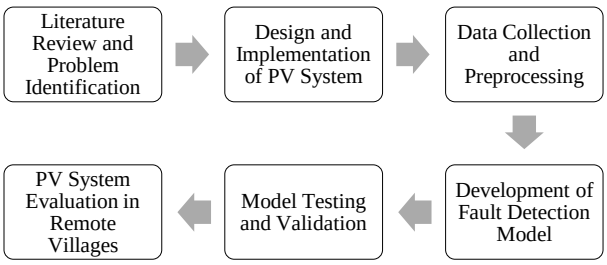



Fig. 1. Research phase.

Data collection and preprocessing were carried out over a specified period to identify operational patterns of the photovoltaic (PV) system under both normal and faulty conditions. The process involved, cleaning the data by eliminating anomalies and noise to ensure its accuracy. Afterward, the data was normalized to ensure compatibility with the regression model and categorized based on the operational conditions of the PV system. The collected environmental parameters included solar radiation intensity, air temperature, humidity, wind speed, rainfall, and panel

temperatures (both top and bottom). The total number of data points for 276 rows with 6 attributes each was 1656 data.

The development of the fault detection model for the photovoltaic (PV) system involved several stages, starting from the system setup to the implementation of the fault detection mechanism. Initially, the necessary hardware components, including photovoltaic panels, solar charge controllers, batteries, inverters, and MCBs, were configured. Environmental parameters such as solar radiation, temperature, wind speed, and rainfall, along with system parameters like current, voltage, power, and temperature at various points in the system, were continuously monitored. The fault detection system was designed to trigger alerts based on FMLR and presented in Fig. 2.

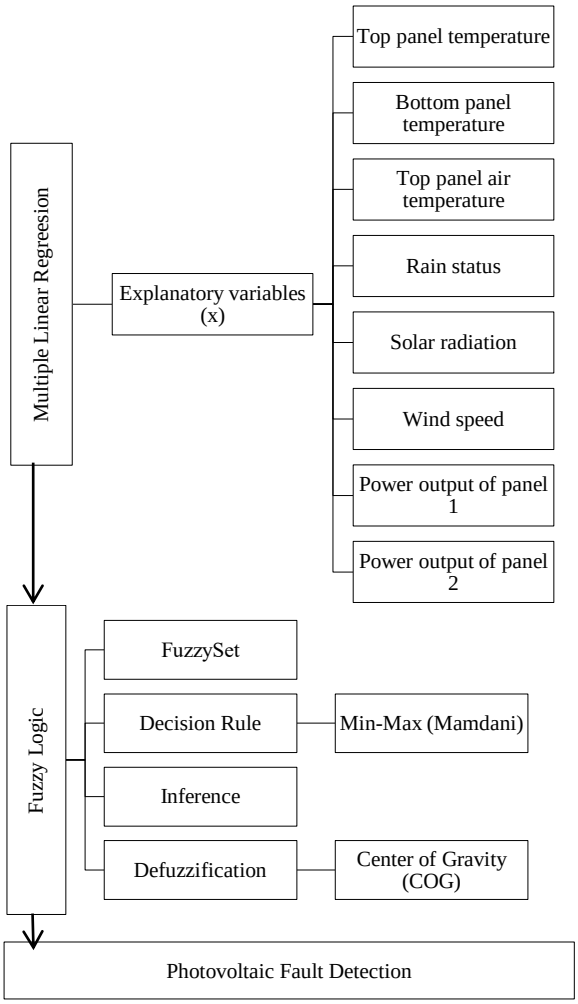



Fig. 2. Photovoltaic fault detection based on FMLR.

The research was conducted using an experimental method by implementing PV system integrated with fault detection. The study took place in Pandan Arang Village, Kandis District and Ogan Ilir Regency with its located in South of Sumatera. Data was collected over a specific period to identify operational patterns in both normal and faulty conditions. This data was preprocessed by eliminating anomalies, normalizing values for compatibility with the regression model, and categorizing it based on operational conditions.

The fuzzy-based multiple linear regression (FMLR) model was designed to enhance the fault detection process in photovoltaic (PV) systems by analyzing the relationships between various environmental and system parameters. These parameters include temperature, solar irradiance, wind speed, humidity, and power output, which directly influence the performance of the PV system. The FMLR model incorporates fuzzy logic to handle uncertainties and nonlinearities in these parameters, offering a more flexible and dynamic approach compared to traditional methods.

The model was trained using historical data collected from the PV system, which included instances of both normal operation and various types of faults. By processing this data, the model learned to identify distinct patterns associated with typical system behavior as well as fault conditions. The use of fuzzy logic rules allowed the model to adapt to varying operational conditions and gradually transition between different system states, rather than relying on rigid, predefined thresholds. This adaptability makes the FMLR model particularly useful for systems that operate in dynamic and unpredictable environments, such as those found in remote or off-grid locations.

Once trained, the FMLR model was able to classify system conditions into several categories, each reflecting a different state of operation. These categories included “Optimal Charging”, where the system is functioning at peak efficiency, “Adjusted Charging”, which occurs when external factors such as weather conditions require adjustments to the charging process, “Charging Delay”, which is triggered when system temperatures are too high to ensure safe operation, and “Fault Alert”, which indicates that a significant fault has been detected, requiring immediate attention.

The developed model underwent testing and validation using test data to assess its accuracy. The fault detection results were compared with manual PV system inspections to validate the model’s accuracy. The fault detection system was deployed and observed in a remote village in South of Sumatera for to detect fault conditions in real-time.

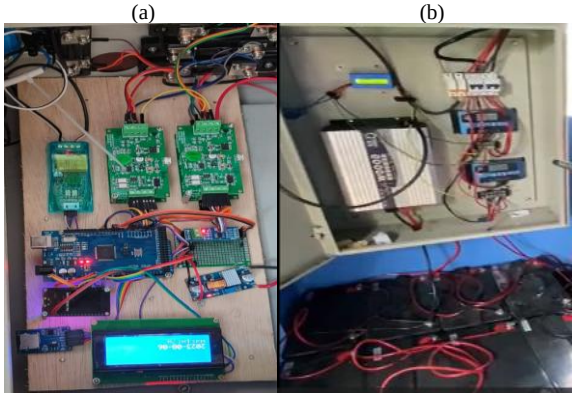
## IV. Research Result

The identification process carried out through a site survey for the placement of the photovoltaic system resulted in the required photovoltaic (PV) components amounting to 6 x 200 WP. The required solar charge controller (SCC) was 2 x 12V 60A, while the battery capacity needed was 8 x 12V 100Ah. Additionally, a single inverter unit with a capacity of 12V 6000-watt peak (WP) was used to support the system. The photovoltaic (PV) panels were installed on top of a water storage tank, arranged in parallel configuration using six panels.

The installation of the PV system followed a parallel PV configuration, where the panels were placed on the roof (rooftop) above the water storage tank. The PV panels were connected to a miniature circuit breaker (MCB) as a protective device before being linked to the solar charge controller (SCC). The SCC was set according to the battery voltage to optimize charging efficiency. From the SCC, the energy was stored in batteries, which were then connected to the inverter. The

inverter was also linked to an MCB before converting DC (Direct Current) into alternating current (AC) to power the water pump. The proposed PV system as illustrated in Fig. 3.

(a) (b)



(c) (d)

Fig. 3. PV system in remote areas (a) Solar panels (b) Solar panels integrated to water storage tank (c) IoT for environment paramater control (d) IoT for PV system control.

The implementation of this system ensured that the photovoltaic system provided a stable energy supply for operating essential equipment in the remote area. The use of the Internet of Things (IoT) allowed real-time monitoring and control of the system, enabling efficient management of power generation and consumption. This approach contributed to improving access to renewable energy in isolated rural areas of South Sumatra, where conventional electricity sources were limited or unavailable.

The photovoltaic fault detection for the PV system was designed to optimize the battery charging process by considering various environmental factors and the output power from solar panels. This system integrated sensors, an Arduino Mega, data storage, and fuzzy-based multiple linear regression (FMLR) to provide more accurate decisions regarding photovoltaic fault detection based on battery charging conditions.

The DSS utilized sensors to collect real-time data on environmental parameters such as solar radiation, temperature, and battery voltage. These data were then processed using an Arduino Mega microcontroller, which acted as the main control unit for data acquisition and transmission. The multiple linear regression (MLR) approach was used to predict the output power of photovoltaic in panel 1 (P1) and panel 2 (P2) by utilizing six independent variables, including top panel temperature ($X_1$), bottom panel temperature ($X_2$), panel surface temperature ($X_3$), rain status ($X_4$), solar radiation intensity ($X_5$) and wind speed ($X_6$). The calculation P1 and p2 using MLR approach is presented in Eq. (4) and Eq. (5).

$$P1 = -1.0389+(0.1656\times X1) + (-0.0754\times X2) + (-0.0688\times X3) + (0.4500\times X4) + (-0.0025\times X5) + (13.6189\times X6) \quad (4)$$

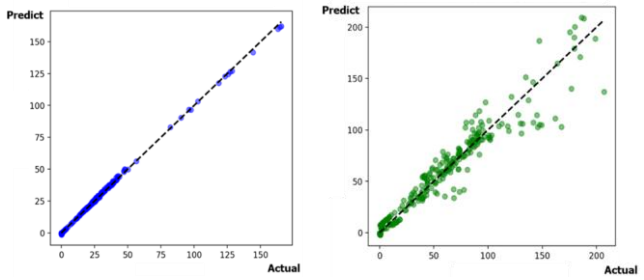
$$P2 = -55.9447+(0.6757\times X1) + (5.0193\times X2) + (-3.5212\times X3) + (-0.9017\times X4) + (0.2040\times X5) + (4.6400\times X6) \quad (5)$$

The fuzzy rules for predicting $P_1$ and $P_2$, along with other input data established several important steps. First, the fuzzy sets for the $P_1$ power output variable and the charging status (P3) variable were defined. Based on the MLR prediction, a fuzzy classification category was generated for predicting $P_1$ and $P_2$, which included three levels: Low, Medium, and High. The classification determined based on fuzzy set values in Table I.

TABLE I. FUZZY SET VALUES

| Variable | Membership | Value Range |
|---|---|---|
| Top Panel Temperature ($X_1$) | Low | ≤ 25°C |
| | Medium | 25°C < T ≤ 35°C |
| | High | > 35°C |
| Bottom Panel Temperature ($X_2$) | Low | ≤ 25°C |
| | Medium | 25°C < T ≤ 35°C |
| | High | > 35°C |
| Air Temperature ($X_3$) | Low | ≤ 25°C |
| | Medium | 25°C < T ≤ 35°C |
| | High | > 35°C |
| Rain ($X_4$) | Rain | 1 |
| | No Rain | 0 |
| Solar Radiation ($X_5$) | Low | ≤ 10 W/m² |
| | Medium | 10 < W/m² ≤ 100 W/m² |
| | High | > 100 W/m² |
| Wind Speed ($X_6$) | Low | ≤ 1 m/s |
| | Medium | 1 < m/s ≤ 3 m/s |
| | High | > 3 m/s |
| Power Output Panel 1 ($P_1$) & Power Output Panel 2 ($P_2$) | Low | ≤ 50 Watt |
| | Medium | 50 < Watt ≤ 100 Watt |
| | High | > 100 Watt |

The comparison graph between actual data and the multiple linear regression (MLR) model predictions illustrated the relationship between observed power output values and the predicted values generated by the model. The first graph presented the actual data for $P_1$ (x-axis) against the predicted $P_1$ values (y-axis), where the blue scatter points were closely aligned with the dashed diagonal line (y = x). This pattern indicated that the model had achieved high accuracy, with minimal error in predicting $P_1$. Meanwhile, the second graph compared actual $P_2$ data (x-axis) with its predicted values (y-axis), where the green scatter points appeared more dispersed, though they still largely followed the y = x diagonal line. The visualizations provided insight into the prediction accuracy and reliability of the MLR model is depicted in Fig. 4.




(a) (b)

Fig. 4. Comparison of actual data and MLR model predictions for (a) panel P1 (b) panel P2.

In a photovoltaic system, the value of the battery charging status (P3) functioned to regulate the battery charging level by considering various environmental factors and the operational conditions of the solar panels. This process used fuzzy logic, which enabled the system to dynamically adjust charging decisions based on input values that were not always precise or binary. Fuzzy logic worked by translating environmental variables such as temperature, solar radiation, wind speed, and rainfall into linguistic categories like low, medium, or high. Then, the system applied fuzzy rules in the form of IF-THEN statements, which determined P3 based on the combination of existing variables and represented through pseudocode, as shown in Fig. 5 (Algorithm 1).

**Algorithm 1**: Decision Rule for PV Fault Detection

```
BEGIN
  INPUT P1, P2, X4, X1, X2, X3, X5, X6

      IF P1 == "low" AND P2 == "high" AND X4 == "no" AND X1
      == "high" AND X2 == "high" AND X3 == "high" AND X5
      == "high" AND X6 == "medium" THEN
      P3 = "Optimal Charging"
      END IF

      …

      IF P1 == "medium" AND P2 == "medium" AND X4 == "no"
      AND X1 == "medium" AND X2 == "high" AND X3 ==
      "medium" AND X5 == "high" AND X6 == "medium" THEN
      P3 = "Optimal Charging"
      END IF

      IF P1 == "high" AND P2 == "high" AND X4 == "no" AND
      X1 == "high" AND X2 == "high" AND X3 == "high" AND
      X5 == "medium" AND X6 == "high" THEN
      P3 = "Optimal Charging"
      END IF

  DISPLAY "Charging Status: ", P3
END
```

Fig. 5. Decision rule for photovoltaic fault detection.

To understand P3 operated in the photovoltaic system, a logical representation was required to illustrate the relationship between input and output variables based on the defined fuzzy rules. Pseudocode could be used to illustrate how environmental variables such as panel power (P1, P2), rainfall (X4), panel temperature (X1, X2), air temperature (X3), solar radiation (X5), and wind speed (X6) interacted in determining the charging status (P3). Each observed variable combination was processed using IF-THEN rules. With the application of fuzzy rules, the system was able to optimize charging when environmental conditions were favorable, adjust the charging mode in response to external disturbances such as rain, and delay or reduce charging to prevent overheating if the panel temperature became too high.

Based on the applied rules, the fuzzy inference system output in fault detection for photovoltaic operations was categorized into four main conditions. The “optimal charging” condition occurred when environmental conditions supported maximum charging, such as high solar radiation, panel temperature within a safe range, and sufficient wind speed to maintain panel temperature stability. The “adjusted charging” condition was applied when external factors influenced the charging process, such as rain, where the system adjusted the charging mode to remain efficient and safe. The “charging delay condition was implemented when panel temperature was too high, potentially causing overheating, leading the system to automatically delay charging to prevent component damage. The “fault alert” condition was triggered when the system detected issues that could cause malfunctions or damage, such as high panel temperature but low solar radiation, which could indicate problems with the panel or electrical system.

In the defuzzification process, the input used was the fuzzy set obtained from the composition of fuzzy rules. This process aimed to determine a crisp value that represented the system output based on the distribution of membership degrees from the various rules that had been previously applied. One of the most commonly used defuzzification methods was the Center of Gravity (COG), where the output value was obtained by finding the central average of all values within the given range. This method calculated the balance point of the fuzzy membership distribution, ensuring that the final result reflected the most representative value based on the applied fuzzy rules.

If the fuzzy inference system generated membership values for multiple output categories such as Optimal Charging, Adjusted Charging, and Charging Delay, then the defuzzification process determined a crisp value among these categories based on their membership weights. Thus, defuzzification enabled the system to translate fuzzy results into concrete actions, such as determining the charging level or detecting potential errors in the photovoltaic system. The structured output in the Arduino Command Line Interface (CLI) environment provided a clear representation of how the fuzzy-based decision support system (DSS) functioned in real-time fault detection is presented in Fig. 6.

```
==================================================
            DSS FAULT DETECTION
==================================================

Enter value for Top Panel Temperature (X1): 39.99
39.99
Enter value for Bottom Panel Temperature (X2):
40.00
40.00
Enter value for Air Temperature (X3): 40.00
40.00
Is it Raining? (1 = Yes, 0 = No) (X4): 0
0
Enter value for Solar Radiation (X5): 500.00
500.00
Enter value for Wind Speed (X6): 4.03
```

```
4.03

--------------------------------------------------
PREDICTION: FUZZY-BASED MULTIPLE LINEAR REGRESSION
--------------------------------------------------
Predicted MLR Value for P1: 53.4406
Predicted MLR Value for P2: 151.7050
Fuzzy Category for P1: Medium
Fuzzy Category for P2: High

--------------------------------------------------
                CHARGING STATUS
--------------------------------------------------
P3 Status: FAULT ALERT

** WARNING **
Please check the **panel condition, environmental
factors, and system configuration** for possible
issues.
```

Fig. 6. Output of Arduino CLI for fault detection.

Fuzzy inference was a rule-based reasoning process used to determine the output based on input variables that had been classified into membership categories. In the fault detection system for IoT-based photovoltaic operations, the fuzzy inference method was applied to link input variables with the charging level and potential system disturbances based on environmental and operational conditions of the solar panels. The method used for fuzzy inference was the MIN-MAX method. Once all propositions had been evaluated, the output contained a fuzzy set that reflected the contribution of each proposition, as shown in Fig. 7.

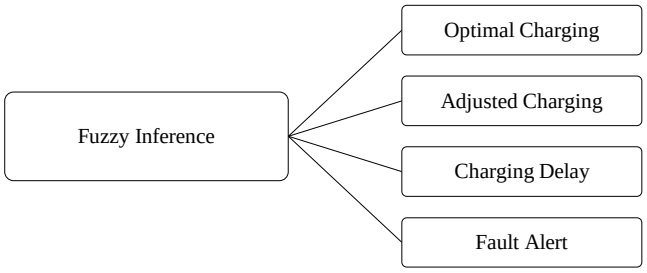



Fig. 7. Fuzzy inference.

The output generated from the Arduino Command Line Interface (CLI) code represented the fault detection process in an IoT-based photovoltaic system using a fuzzy inference model and multiple linear regression (MLR). The system prompted the user to input environmental parameters, including top panel temperature ($X_1$), bottom panel temperature ($X_2$), air temperature ($X_3$), rainfall status ($X_4$), solar radiation ($X_5$), and wind speed ($X_6$). Based on these inputs, the system computed predicted power values ($P_1$ and $P_2$) using the MLR model and classified them into fuzzy categories such as Low, Medium, or High. The final step involved evaluating the charging status (P3) using predefined fuzzy logic rules. If an anomaly was detected, the system triggered a Fault Alert, indicating a potential operational issue within the photovoltaic system. The warning message advised further inspection of panel conditions, environmental factors, and system configurations to prevent potential failures or inefficiencies.

## V. Conclusion

This research successfully developed and implemented a Fault Detection Model for photovoltaic (PV) systems in remote areas, utilizing the Fuzzy-Based Multiple Linear Regression (FMLR) approach. The model demonstrated its potential to address the challenges of monitoring PV systems in regions with limited access to conventional power grids and technical resources. By integrating environmental parameters such as solar radiation, temperature, wind speed, and rainfall, along with PV system parameters like panel voltage, current, battery voltage, and inverter performance, the system effectively tracked and evaluated the operational conditions of the photovoltaic system. The system was successfully deployed in Pandan Arang Village, Kandis District, Ogan Ilir Regency, South Sumatera, Indonesia, providing a reliable and sustainable solution for enhancing the efficiency of renewable energy sources in isolated communities.

Data collection and preprocessing were carefully executed to ensure the quality and accuracy of the data, with anomalies removed, normalization applied, and data categorized based on operational conditions. The MLR model was used to predict the output power of the PV system, while fuzzy logic enabled the handling of uncertainties in data, offering greater flexibility in decision-making. The system utilized fuzzy rules to determine the charging status (P3), categorizing it into Optimal Charging, Adjusted Charging, Charging Delay, or Fault Alert, ensuring adaptive and responsive fault detection. The developed model was tested using real-time data, and its performance was validated against manual inspections, demonstrating its high accuracy and effectiveness in fault detection.

Future research focused on further validating the proposed fault detection model by conducting long-term field studies in various geographical regions with different climatic conditions. This approach helped assess the model's robustness and adaptability in diverse environments. Additionally, the integration of advanced machine learning techniques, such as deep learning, was explored to improve the model's predictive accuracy and real-time fault detection capabilities. Future studies also investigated the optimization of energy storage and grid integration in remote PV systems to enhance the overall efficiency and sustainability of renewable energy solutions.

## Acknowledgment

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# Path Planning Technology for Unmanned Aerial Vehicle Swarm Based on Improved Jump Point Algorithm

Haizhou Zhang*, Shengnan Xu
School of Information Engineering, Henan Vocational University of Science and Technology, Zhoukou, Henan, 466000, China

***Abstract*—Multi-unmanned aerial vehicle path planning encounters challenges with effective obstacle avoidance and collaborative operation. The study proposes a swarm planning technique for unmanned aerial vehicles, based on an improved jump point algorithm. It introduces a geometric collision detection strategy to optimize path search and employs the dynamic window method to constrain the flight range. Additionally, the study presents conflict avoidance strategies for multi-unmanned aerial vehicle path planning and establishes collision fields for unmanned aerial vehicles to achieve collaborative path planning. In single unmanned aerial vehicle path planning, the research model exhibits the lowest control errors in the X, Y, and Z axes, with the Y-axis error being 0.05m. In static planning, the model boasts the shortest planning time and length, with 1002ms and 17.85m in multi-obstacle planning, respectively. In multi-unmanned aerial vehicle path planning, the research model effectively avoids local optimal problems in local conflict scenarios and re-plans the route. During testing on a 29m×29m grid map, the research technology successfully avoids obstacles and re-plans routes. However, similar technological obstacles can cause interference and traps in local convergence, preventing re-planning. The research technology demonstrates good application effects in the path planning of unmanned aerial vehicle swarms and will provide technical support for multi-machine collaborative path planning.**

***Keywords*—Unmanned aerial vehicle swarm; path planning; jump point search algorithm; geometric collision detection; dynamic window method***

## I. INTRODUCTION

With the development of unmanned aerial vehicle (UAV) technology, the potential application of multi-UAV cooperative planning in military reconnaissance, environmental monitoring, disaster rescue, and other fields is enormous. However, the planning for multiple UAVs is constrained by the control of these UAVs and the impact of obstacles, leading to poor coordination among the UAVs and challenges in meeting flight requirements. Therefore, scholars have conducted extensive research on collision planning techniques for UAV swarms to improve the effectiveness of UAV swarm planning [1]. Shen K et al. studied the problem of insufficient path planning (PP) for multi-warehouse UAVs and proposed a PP method that considers collision avoidance. This method optimized the route by establishing a multi-warehouse UAV PP model, taking into account factors such as UAV flight distance, time, and cargo loading capacity. Flight tests showed that this method could reduce UAV costs and improve technical planning efficiency [2]. Meng S et al. conducted research in the field of UAV detection. To improve the coordination effect of multiple UAVs, image denoising technology was introduced to optimize feature extraction and enhance the processing and analysis of object edge details. Tests showed that this technology could substantially raise the obstacle avoidance ability and crack object detection performance of UAVs [3]. Bui S T et al. conducted research on the insufficient adaptability of UAVs for takeoff, landing, and collision, and proposed a biomimetic propeller design for UAVs. This design was inspired by the flexibility and elasticity of dragonfly wings, which can adapt to collisions and quickly recover and hover. Tests showed that the proposed propeller had good adaptability and could effectively optimize the collision effect of UAVs [4]. Fahimi H et al. proposed a vision-based guidance algorithm to enhance the obstacle avoidance capability of UAVs. It was equipped with cameras inside the UAV, which detected object edge details through algorithms, optimized the captured image details using algorithms, and provided flight decisions for UAV obstacle avoidance. The results indicated that UAVs could effectively avoid obstacles in flight scenarios and improve the planning efficiency of UAVs [5].

At present, multi-UAV collaborative PP is a key focus of UAV development. Saeed R A et al. conducted research on PP for UAV swarms. To improve the obstacle avoidance and planning effectiveness of UAVs, a three-dimensional scene multi-UAV planning technology based on ant colony algorithm was proposed, and the technology was improved through conditional constraints and collision strategies. The results indicated that the technology had good planning performance [6]. Puente Castro A et al. studied the problem of insufficient PP for UAV swarms and proposed a solution based on artificial intelligence algorithms. The study conducted research on the latest UAV planning technologies, selected the latest technologies through classification and comparison, and summarized the limitations of current research. The results indicated that artificial intelligence planning scenarios were limited by computation and complex conditions, and had limited adaptability [7]. Dhuheir M A et al. proposed a distributed collaborative inference request and PP model to tackle the problem of insufficient reasoning in UAV PP. This model divided inference requests into multiple parts and executes them in different UAVs to reduce data transmission latency and interference. Experimental tests showed that this technology had good adaptability, but communication and collaboration still faced difficulties [8]. Sharma A et al. studied the PP problem for UAV swarm interception of multiple aerial

*Corresponding Author

targets and proposed a solution based on swarm intelligence algorithm. The team conducted a comprehensive analysis and improvement of swarm intelligence algorithms such as particle swarm optimization (PSO) and ant colony optimization. In practical scenario testing, different algorithms had limited adaptability in complex environments and diverse target interception tasks, and the impact of dynamic obstacle scenarios needed to be considered [9]. Yu Z et al. proposed a new hybrid PSO algorithm for automatic PP of UAVs. This algorithm improved the global optimal solution update strategy and particle learning strategy of PSO algorithm by integrating simulated annealing algorithm, enhancing optimization ability and convergence speed. Experimental tests showed that the proposed technology could adapt well to the 3D scene planning effect of UAVs [10].

In summary, multi-UAV planning is the key to the development of UAV technology. However, PP for multiple UAVs is more complex, and how to avoid obstacles and coordinate the fleet is a technical challenge. At present, technologies such as ant colony algorithm, particle algorithm, and bat algorithm have good advantages in PP, but they still face problems such as high computational cost and insufficient planning for complex dynamic scenes in multi-UAV scenarios. Therefore, in order to solve the problem of insufficient PP for UAV swarms, an intelligent UAV swarm PP technology based on an improved Jump Point Search (JPS) algorithm is proposed. There are two innovations in this technology. Firstly, the introduction of geometric collision detection strategy in the research improves the shortcomings of JPS node search. Meanwhile, Dynamic Window Approaches (DWA) are introduced for obstacle avoidance optimization to enhance the accuracy of PP. Secondly, the research focuses on adding conflict avoidance strategies in multi-UAV PP, setting avoidance specifications through the division of collision fields, and enhancing the obstacle avoidance capabilities of UAV swarms. The research has two contributions. One is that the technology provides technical support for single UAV PP and improves its ability of obstacle avoidance and dynamic planning in complex environments. The second is that the research provides technical support for the cooperative operation of multiple UAVs, and helps the UAV cluster to effectively coordinate and avoid conflicts in complex tasks.

## II. Methods and Materials

### A. Modeling of Single UAV PP Based on Improved JPS

The process of UAV PP needs to consider various threats and limitations in the environment to avoid collisions during flight. Therefore, the PP modeling of single UAV based on improved JPS algorithm is studied. Aiming at the environmental threat and collision risk in UAV PP, the improved JPS algorithm is introduced as the global planning technology, and combined with DWA algorithm to optimize the local planning. The JPS algorithm, which is based on a grid map, employs the JPS strategy to identify feasible nodes and optimizes the path using a geometric collision detection strategy. DWA algorithm can adjust the speed and direction of UAV in real time and improve the effect of dynamic planning by constructing speed space and dynamic window. The entire technical process is shown in Fig. 1.

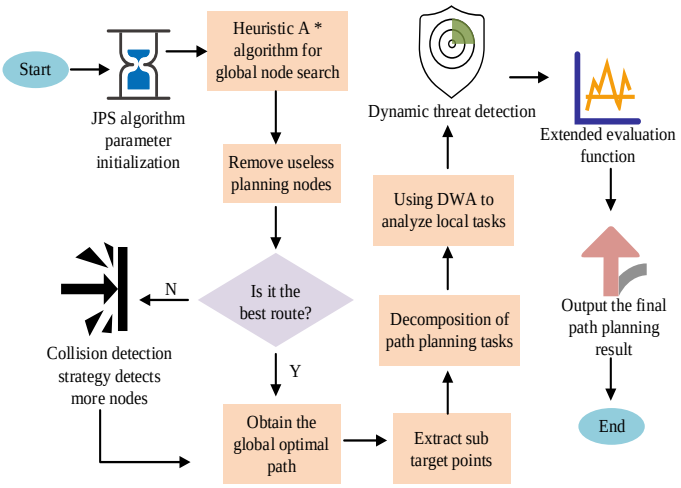


Fig. 1. Single UAV PP technology.

From Fig. 1, this technology uses the JPS algorithm as the global PP core, while adopting DWA as the local planning to improve the dynamic planning effect of UAVs. In the scope of UAV planning, JPS is used to obtain feasible nodes, based on a grid map, where each grid contains 8 adjacent nodes. The JPS algorithm needs to remove useless nodes based on the adjacent node pruning strategy in order to search for the best planned path [11]. The evaluation function $R(n)$ is shown in Eq. (1).

$$R(n)=g(n)+h(n) \tag{1}$$

In Eq. (1), $h(n)$ represents the cost incurred from node $n$ to the target node. $g(k)$ represents the optimal actual path cost from the initial to the current node $n$. In actual UAV planning, the JPS algorithm is affected by the expansion direction of grid nodes, and its planning can only choose 8 speed directions, which will significantly limit its planning effectiveness [12]. In this regard, the study introduces geometric collision detection strategies to optimize its planned path, thereby providing more selectable paths for UAVs. Among them, if the optional path is defined as $\pi' = (n_1, n_7, n_8)$, $n_i$ is the path node, and the original path is $\pi = \{n_1, n_2, \cdots, n_8\}$, then the collision detection strategy is expressed as Eq. (2) [13].

$$\kappa(n_i, n_j) = \begin{cases} (n_i, n_j) & 0, \\ (n_i, n_j) & 1, \end{cases} \quad \forall n_1, n_j \in N \tag{2}$$

In Eq. (2), $\kappa(\square)$ is the detection function, $n_i$ and $n_j$ both are nodes within the original path set $N$. The study employs a collision detection strategy to identify nodes in the original path where collisions occur, represented as 1, and those without collisions, represented as 0. The principle of collision detection strategy path optimization is shown in Fig. 2 [14].

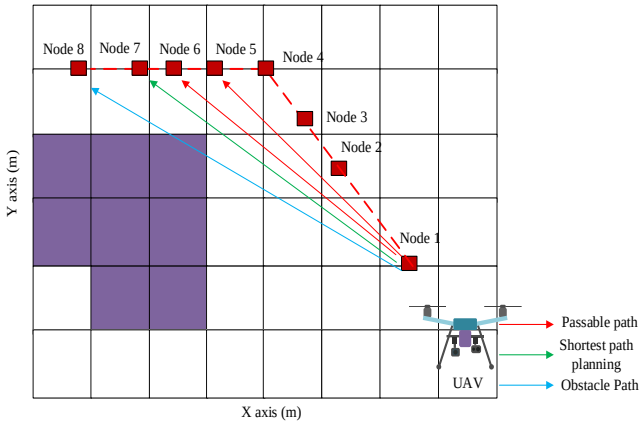


Fig. 2. Schematic diagram of collision detection strategy.

According to Fig. 2, in the original path search, this strategy identifies optional paths through geometric collisions to avoid obstacles. In addition, the study introduces the DWA algorithm as a local obstacle avoidance planning technique for UAVs, which has fast response and low computational complexity. In UAV collision control, it is necessary to construct a UAV motion model, as shown in Eq. (3).

$$\begin{cases} \xi(t_n) = \xi(t_0) + \omega(t)\Delta t \\ x(t_n) = x(t_0) + \int_{t_0}^{t_s} v(t)\cos\left[\theta(t)\right]dt \\ y(t_n) = y(t_0) + \int_{t_0}^{t_s} v(t)\sin\left[\theta(t)\right]dt \end{cases} \quad (3)$$

In Eq. (3), $\xi(t_n)$ represents the angle between the UAV and the X-axis at time $t_n$. ($x(t_n), y(t_n)$) is the coordinate of the UAV at time $t_n$. To satisfy the demands of UAV, it needs to satisfy motion model constraints, as shown in Eq. (4) [15].

$$\begin{cases} DS(x,y) \geq 0 \\ 0 \leq v \leq v_{\max} \\ \omega_{\min} \leq \omega \leq \omega_{\max} \\ \dot{v}_b \leq \dot{v}_{b\max} \end{cases} \quad (4)$$

In Eq. (4), $DS(x,y)$ represents the closest distance between the obstacle and the UAV. $v$ indicates the linear velocity of the UAV. $\omega$ is the angular velocity of UAVs. $\dot{v}_b$ is the braking acceleration of the UAV's linear velocity. To ensure that the UAV maintains optimal planning performance within the constraint range, the DWA algorithm needs to construct a velocity space based on the UAV's own coordinates, as shown in Fig. 3 [16].

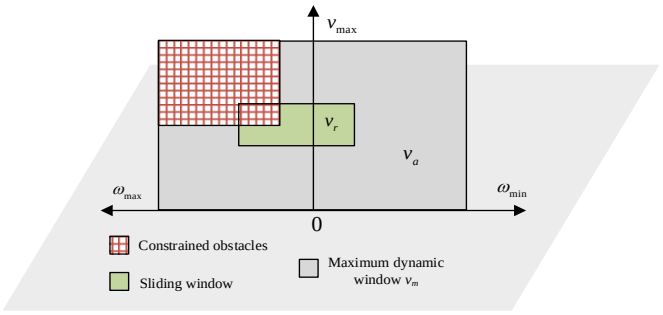


Fig. 3. UAV speed space.

In Fig. 3, a velocity space is established with the origin of the UAV as the coordinate, where the angular velocity is represented by the horizontal axis and the vertical axis is represented by the UAV linear velocity. When a UAV performs a flight mission, any cycle command is represented by $(v, \omega)$ and the UAV velocity space is composed of multiple $(v, \omega)$. The dynamic window is the speed range that the UAV can reach in the speed space [17]. The maximum dynamic window of the UAV is defined as $V_m$, expressed as Eq. (5).

$$V_m = \{(v,\omega) | 0 \leq v \leq v_{\max}, \omega_{\min} \leq \omega \leq \omega_{\max}\} \quad (5)$$

In an effective planning process, the UAV's speed is limited to prevent collisions with objects; upon a collision, the speed will drop to zero. The maximum dynamic window of the aircraft within the safe range is set as $V_{safe}$, as shown in Eq. (6) [18].

$$V_{safe} = \left\{(v,\omega) | v \leq \sqrt{2DS(v,\omega)\dot{v}_{b\max}}, \omega \leq \sqrt{2DS(v,\omega)\dot{\omega}_{b\max}}\right\} \quad (6)$$

In Eq. (6), $DS(v,\omega)$ is the distance between the UAV and the obstacle. $\dot{\omega}_{b\max}$ represents the maximum angular velocity braking acceleration of the UAV. Besides, the maximum speed of the UAV planning is influenced by its own acceleration capabilities, which further narrows the range of the maximum dynamic window $V_m$, particularly during obstacle avoidance when the speed is kept at a low level. [19]. Therefore, based on this, the dynamic window $V_F$ is obtained as shown in Eq. (7).

$$V_F = \{(v,\omega) | v_c - \dot{v}_{b\max}\Delta t \leq v \leq v_c + \dot{v}_{a\max}\Delta t, \omega_c - \dot{\omega}_{b\max}\Delta t \leq \omega \leq \omega_c + \dot{\omega}_{a\max}\Delta t\} \quad (7)$$

In Eq. (7), $\omega_c$ represents the current angular velocity of the UAV, $\dot{\omega}_a$ is the maximum angular acceleration of the UAV, $v_c$ is the current line velocity of the UAV, and $\dot{v}_{a\max}$ represents the maximum linear acceleration of the UAV. Based on the above analysis, the optional velocity space $V_r$ for the UAV planning process can be obtained, as shown in Eq. (8).

$$V_r = V_m \cap V_{safe} \cap V_F \tag{8}$$

After determining the final optional speed space, the study assumes that the UAV's speed is short and constant, and therefore the impact of acceleration on the UAV can be ignored. In a shorter UAV planning time, if the UAV planning presents a straight line, the UAV trajectory prediction can be obtained based on the UAV motion model, as shown in Eq. (9) [20].

$$(F_x^i - O_x^j)^2 + (F_y^i - O_y^j)^2 = (r_F)^2, \omega_i \neq 0 \tag{9}$$

In Eq. (9), $(O_x^j, O_y^j)$ is the center coordinate of the UAV's motion trajectory. $r_F$ represents the center coordinate radius of the UAV. $F_x^i$ and $F_y^i$ are the horizontal and vertical axis dynamics of the center coordinate point of the UAV. Based on the short and constant speed, the predicted trajectory of the UAV can be obtained, as shown in Eq. (10).

$$\begin{cases} r_F = \left| \dfrac{v_i}{\omega_i} \right| \\ O_x^i = -\dfrac{v_i}{\omega_i} \cdot \sin\theta(t_i) \\ O_y^i = \dfrac{v_i}{\omega_i} \cdot \cos\theta(t_i) \end{cases} \tag{10}$$

In Eq. (10), $t_i$ represents the predicted time. Next, the research needs to evaluate the predicted trajectory of UAVs. If the high score instruction $(v, \omega)_{\max}$ of the UAV is taken as the next sampling control instruction of the UAV, the direction evaluation function is obtained as shown in Eq. (11).

$$F(v,\omega)_{\max} = \sigma\left[\tau \cdot DS(v,\omega) + \gamma \cdot vel(v,\omega) + \varepsilon \cdot HD(v,\omega)\right] \tag{11}$$

In Eq. (11), $\sigma$ represents normalization processing. $\gamma$, $\varepsilon$, and $\tau$ are both evaluation weight coefficients. $vel(v,\omega)$, $DS(v,\omega)$, and $HD(v,\omega)$ respectively represent speed, distance, and direction evaluation functions.

### *B. PP Modeling Based on Multiple UAV Swarms*

The previous chapter completed the PP for a single UAV, and the control of UAV swarms has evolved from single-UAV to multi-UAV control, which is subject to more conditional constraints and involves more complex control. For the collision risk and complex planning requirements of multi-UAV cooperative operation, the collision avoidance strategy and collision field division are introduced to solve the potential conflicts between UAVs. Upon analyzing the limitations of forward trajectory prediction and the dynamic window of UAVs, an optimization scheme based on detection radius and information sharing is proposed. A detailed conflict quantification standard is also formulated, encompassing avoidance rules in the front, back, left, right, and upward directions, thereby effectively enhancing the collaborative planning ability and obstacle avoidance performance of the UAV cluster. The multi-machine planning process requires collaborative work to avoid cluster collisions. The difference between single UAV and UAV swarm planning is shown in Fig. 4.

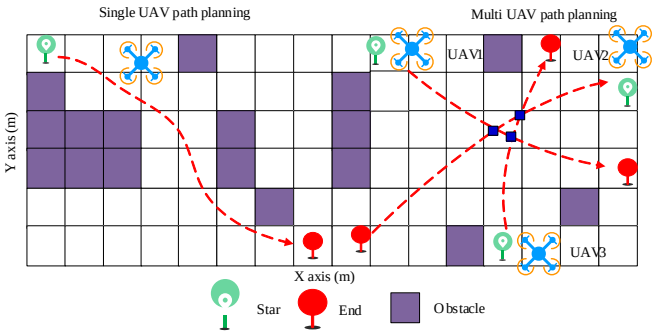


Fig. 4. UAV swarm PP and single UAV PP.

According to the scenario of unmanned cluster planning depicted in Fig. 4, multiple UAVs must navigate to avoid obstacles while not interfering with other UAV operations, all under multiple constraints and within a more complex framework. The single machine planning method obviously does not meet the requirements of collaborative control between UAVs. Therefore, the study introduces UAV conflict avoidance strategies for UAV conflict control. In the conflict analysis of UAVs using the JPS algorithm, it is assumed that the forward trajectory prediction time for all individual machines in the UAV fleet is the same, which is $t_i$. When the predicted trajectory distance is lower than the safe distance set by the cluster system, it is considered as a flight conflict. If there is an overlap in the predicted trajectories of multiple UAVs, it indicates that the current UAV will have a flight conflict [21]. Considering that the dynamic window in UAV planning only predicts conflicts at forward time $t_i$, and does not consider the impact on the UAV's own farther distance, the study also introduces collision fields to solve this problem, as shown in Fig. 5.

In Fig. 5, the red inner circle area represents the entire area of UAV safety conflict. UAVs in the red area will not collide, that is, $0 \le d \le r_1 + r_2$. $d$ is the distance between the UAV and the center point, and $r_1 + r_2$ is the radius distance between the two UAVs. When the UAV exceeds the detection range, that is, $d > r_{rule}$, $r_{rule}$ is the detection radius of UAVs 1 and 2, and the green area indicates that the UAV is beyond the recognizable green range, and the UAV is in a low-risk conflict area. If the UAV is within the green range, it is an avoidance area, and there may be potential conflicts within this range. According to the detection of two UAVs moving in the same straight line, the detection radius $r_{rule}$ can be obtained, as shown in Eq. (12).

$$r_{r_{ule}} = r_1 + r_2 + (v_1 + v_2) \cdot t_i \tag{12}$$

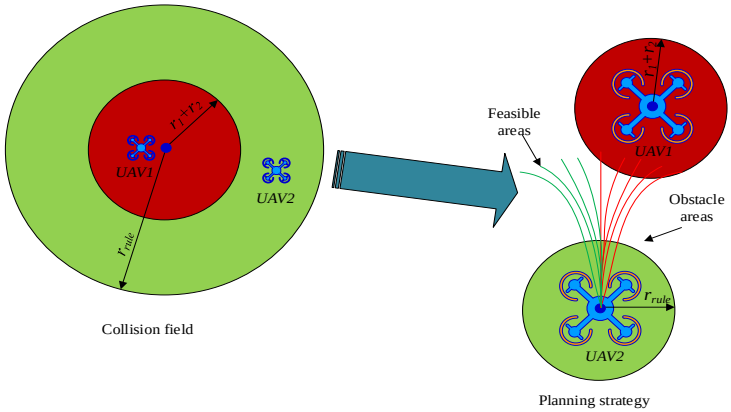


Fig. 5. Division of UAV collision field.

In Eq. (12), $v_1$ and $v_2$ are the linear velocities of UAVs 1 and 2, respectively. To ensure that UAVs can detect objects and escape in a timely manner before conflicts occur, research needs to use the maximum value of $r_{rule}$ as the detection radius for all UAVs in the fleet. In addition, the inability to use velocity space to predict dynamic obstacle trajectories during UAV flight can lead to local optimal planning problems in UAV planning, as shown in Fig. 6 [22].

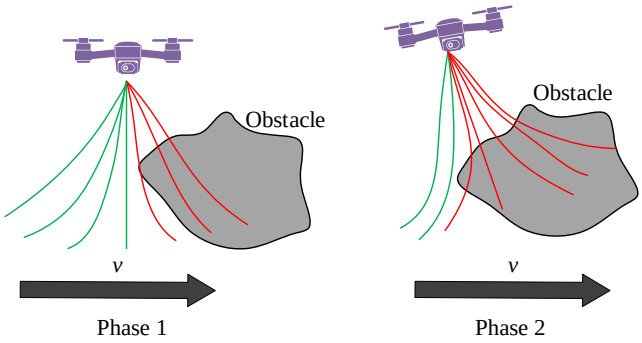


Fig. 6. Dynamic obstacle UAV planning scenario.

From stage 1 in Fig. 6, the UAV will select a green safe trajectory for planning to avoid dynamic obstacles ahead. However, in the second stage, if the obstacle movement speed is equal to or greater than the planned speed of the UAV, it will result in its inability to effectively yield to the obstacle [23]. At this moment, the UAV can only decelerate and evade, awaiting the lifting of the speed space limit. The UAV can maintain its original planned route or turn right to take a detour. To avoid such problems, the research adds a cluster information exchange mechanism, which means that different UAV motion states are shared with each other, providing an effective selectable speed space for the next UAV in advance [24]. Meanwhile, flight planning is carried out according to conflict avoidance rules, including conflicts in the front, rear, left, and right directions. The quantification standard for forward conflicts is shown in Eq. (13).

$$|\ell_{cg}| < \frac{\pi}{36} \tag{13}$$

In Eq. (13), $\ell_{cg}$ represents the azimuth angle of unmanned aerial vehicl $UAV_c$ e relative to the current UAV $UAV_g$. If $UAV_c$ is located in front of $UAV_g$, there will be two situations where the UAV flies in the same or opposite direction. Regardless of which scenario, $UAV_c$ remains in its original state, while $UAV_g$ uses left or right planning to avoid obstacles [25]. The quantification standard for the right side conflict is shown in Eq. (14).

$$-\frac{5}{8}\pi \le \ell_{cg} < -\frac{\pi}{36} \tag{14}$$

In the right side conflict, $UAV_c$ is located to the right of $UAV_g$ and has the highest flight priority. Currently, UAV $UAV_g$ needs to slow down or turn left to avoid. The left side conflict quantification standard is shown in Eq. (15) [26].

$$\frac{\pi}{36} \le \ell_{cg} < \frac{5}{8}\pi \tag{15}$$

In the left side conflict, $UAV_c$ is located to the left of $UAV_g$, which has the highest flight priority. The conflicting UAV $UAV_c$ needs to slow down or turn right to avoid. The quantification standard for post burst is shown in Eq. (16).

$$|\ell_{cg}| \ge \frac{5}{8}\pi \tag{16}$$

In the rear conflict, $UAV_c$ is located behind $UAV_g$, and $UAV_g$ also has the highest flight priority. It maintains its original flight state unchanged, while aircraft $UAV_c$ takes the initiative to avoid to the left or right.

## III. RESULTS

### A. Single Machine PP Experiment

Next, the research conducted experiments on the proposed UAV PP technology, setting the UAV flight experiment scene to various specifications of grid maps, including 30m×30m, 38m×38m, etc. Meanwhile, in the implementation of UAV flight PP, experiments were conducted by dividing static and dynamic obstacle scenarios. The details of the experimental hardware setup are presented in Table I.

In the experimental analysis, common UAV planning algorithms A* and JPS were introduced as tests to confirm the validity of different techniques in regard to control error, planning length, number of expansion nodes, and planning duration. The study selected a 38m×38m grid map environment for UAV flight control experiments, and the test outcomes are in Fig. 7.

TABLE I DETAILS ABOUT THE EXPERIMENTAL SETUP

| Experimental environment | Model |
|---|---|
| Experimental System Platform | Windows 11 |
| Experimental processor | AMD 3800X |
| Graphics card | NVIDIA RTX3070 |
| Computer operating memory | 32 RAM |
| Hard disk capacity | 1T |
| Simulation experimental platform | MATLAB |

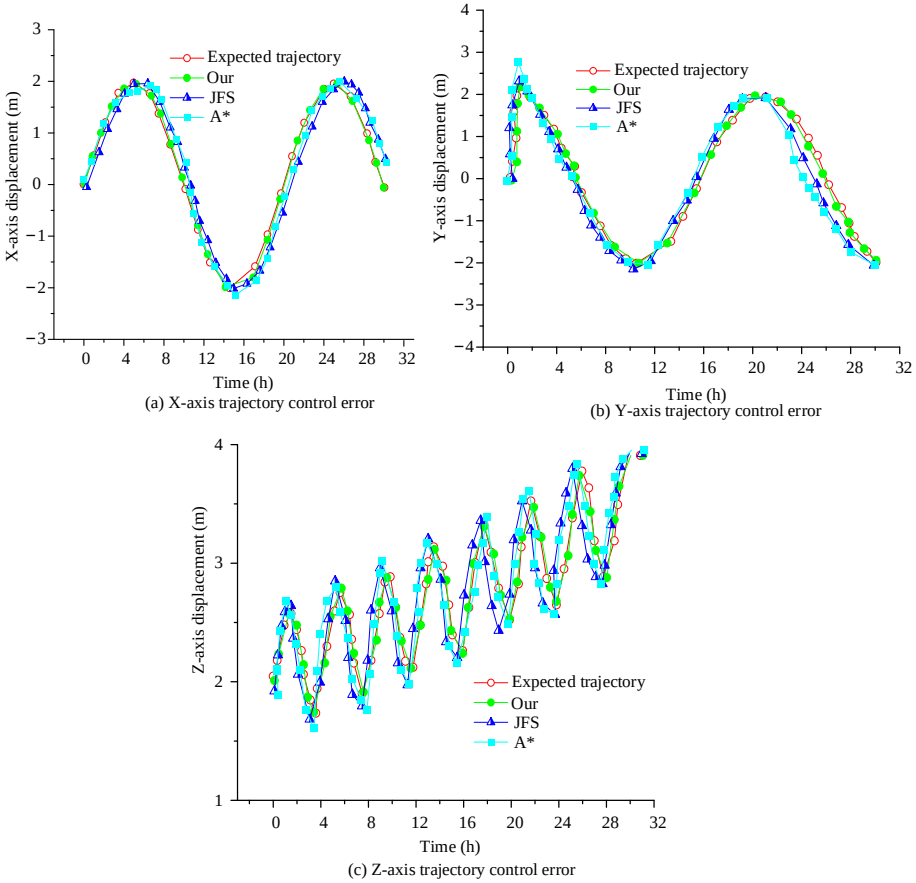


Fig. 7. Experimental analysis of flight control error for a single UAV.

Fig. 7(a) shows the control error of the UAV in the X-axis direction. According to the curve changes, at the 32nd hour of the UAV flight, the expected trajectory in the X-axis was -0.020m, the research model was -0.0019m, while JPS and A* were 0.4984m and 0.4935m, respectively. Overall, the control error of the research model was lower, with an improvement of 7.25% and 9.28% in accuracy compared to the JPS and A* control errors. Fig. 7(b) shows the analysis outcomes of the control error of the UAV in the Y-axis direction. At the 2nd and 26th hours of flight, A* and JPS had significant deviations in control accuracy and predicted trajectory in the Y-axis direction. In the second hour, A* planning was unable to effectively screen out effective planning nodes, resulting in them exceeding the expected trajectory by 0.56m. Meanwhile, JPS also exceeded the expected trajectory by 0.25m. Only the research model controlled the error at 0.12m, resulting in better overall control accuracy. Fig. 7(c) shows the control error of the UAV in the Y-axis direction. Only the research model could follow the expected trajectory well, with an overall deviation controlled within the range of 0.05m. However, A* flight planning was the worst, such as in UAV turning scenarios at the 4th and 8th hours, where A*'s following control was significantly insufficient. JPS also faced similar problems. Next, a 30m×30m grid map was selected for static scene planning testing, and the test results are shown in Fig. 8.

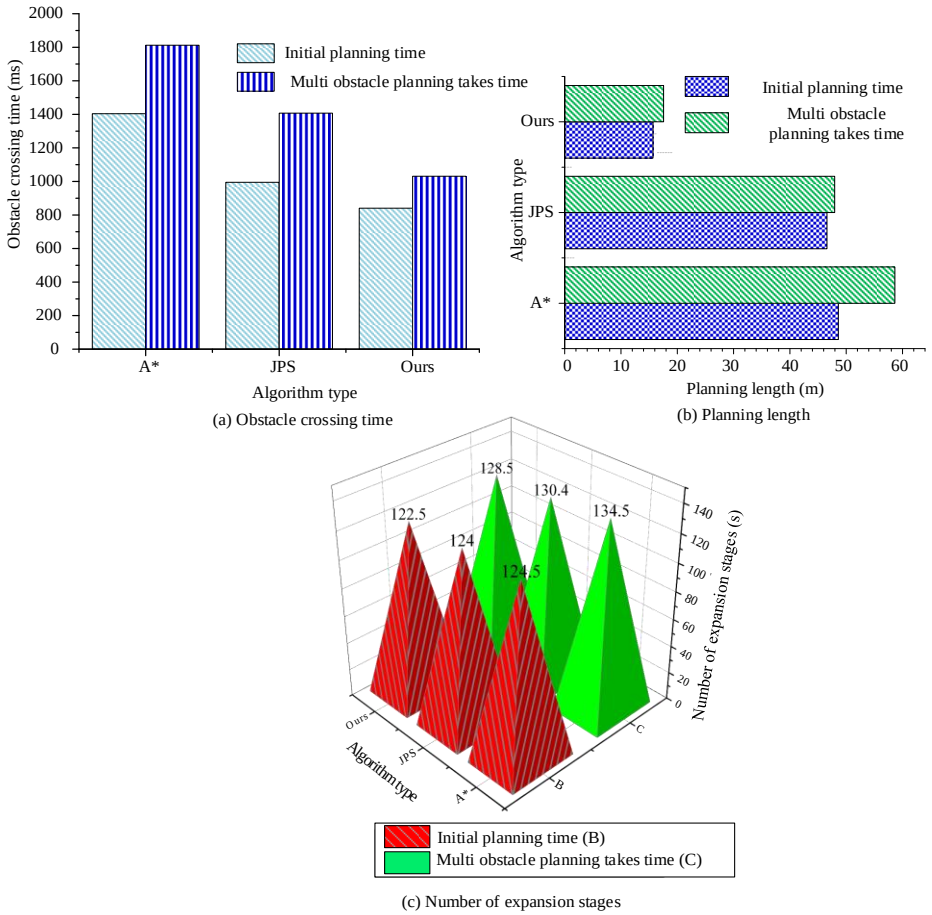


Fig. 8. Comparison of comprehensive effects of static PP for UAVs.

Fig. 8(a) shows the comparison of obstacle crossing time. In the initial planning, A* took 1401ms, JPS was 1002ms, and the research model was 885ms. However, in the multi-obstacle planning, the overall time of the research model was the shortest, only 1002ms. The comparison of PP length is shown in Fig. 8(b). The research model had the lowest planning length in both the initial planning and multi-obstacle planning, which were 15.25m and 17.85m, respectively, while JPS and A* had planning lengths of 49.85m and 58.054m, respectively. Fig. 8(c) shows the comparison of the number of extended nodes in PP. The research model had a significantly lower number of extended nodes in PP, with 122.5 nodes in the research model, 124.5 nodes in A*, and 124.0 nodes in JPS. In multi-obstacle planning, the research model had 128.5 extended nodes, which was significantly lower than the other two techniques. This indicated that it had lower resource utilization and better planning efficiency in planning. Finally, a 38m×38m grid map was selected for PP testing, as shown in Fig. 9.

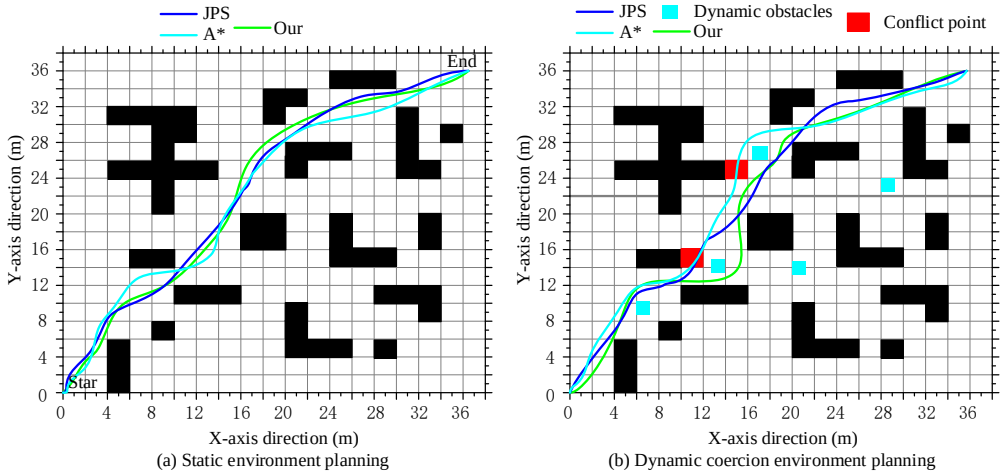


Fig. 9. Static and dynamic obstacle PP test.

Fig. 9(a) shows the results of static environmental PP, where the UAV crossed obstacles from the starting point to the endpoint. The final planned length of the research model was 59.2m, while JPS was 61.2m and A* was 63.2m. Fig. 9(b) shows the results of dynamic obstacle planning scenarios. The blue area represents dynamic obstacles, and the red area represents conflict points. According to the results, A* experienced two conflicts during the planning process, which led to an increase in both its planning length and time. Meanwhile, JPS also encountered conflicts with the first dynamic obstacle, necessitating avoidance maneuvers. The final planned lengths of JPS and A* were 68.2m and 70.2m, respectively. However, the research model effectively predicted the trajectory of dynamic obstacles and avoids waiting, with the shortest planned distance being 63.28m.

### B. UAV Swarm PP Experiment

Next, the research continued to test the PP of multi-person airport scenery, with consistent experimental environments. The research compared DWA-JPS with DWA-JPS that combined conflict avoidance strategies (Ours). Firstly, the study selected local planning quantities for UAV conflict planning for testing, as shown in Fig. 10.

Fig. 10(a) and 10(b) show the conflict planning results of DWA-JPS and Ours, respectively. In the DWA-JPS planning, both forward-moving UAVs opted to evade obstacles by veering left and right, which led to both UAVs altering their intended destinations and becoming trapped in local optima, rendering it impossible to re-plan their predestined trajectories. In Ours conflict planning, the two UAVs adopted a conflict avoidance strategy, successfully separated and detoured back to their original trajectory. Next, a 30m×30m grid map was selected for multi-UAV planning testing, as shown in Fig. 11.

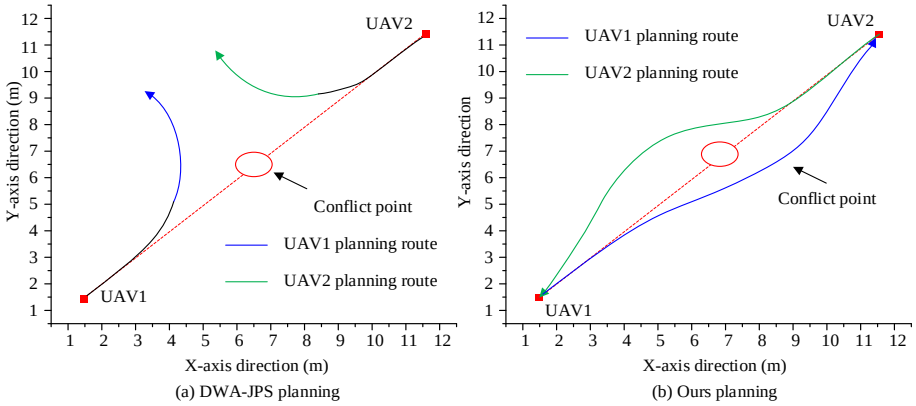


Fig. 10. Local conflict planning test.

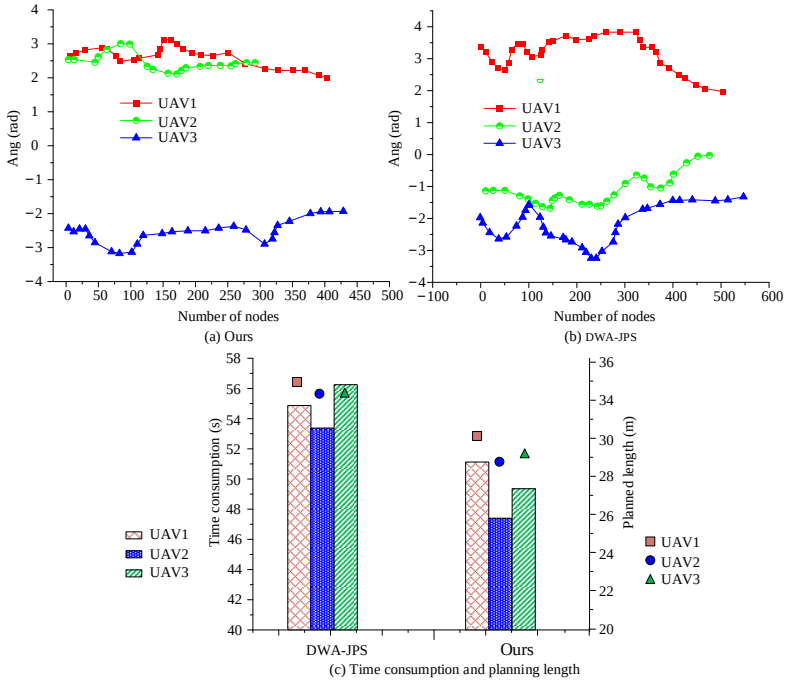


Fig. 11. Multi-UAV planning test.

Fig. 11(a) and 11(b) show the PP of Ours and DWA-JPS, respectively. There were significant differences in the planning angles between the two types of UAVs, but the number of expansion nodes in Ours planning was significantly lower. For example, in Ours planning, UAV 2 had 324 expansion nodes, while DWA-JPS had 501. Fig. 11(c) shows the results of time consumption and planning length. According to the results, the average time consumption in DWA-JPS planning was 55.2s, while Ours was 49.8s, indicating that the research model had a shorter planning time. In the comparison of planning lengths, the average planning length of Ours was 29.3m, while that of DWA-JPS was 55.3m. The planning technology proposed in the study performed better overall. Finally, the study selected 19m×19m and 29m×29m grid maps for comparison of planning effects, as shown in Fig. 12.

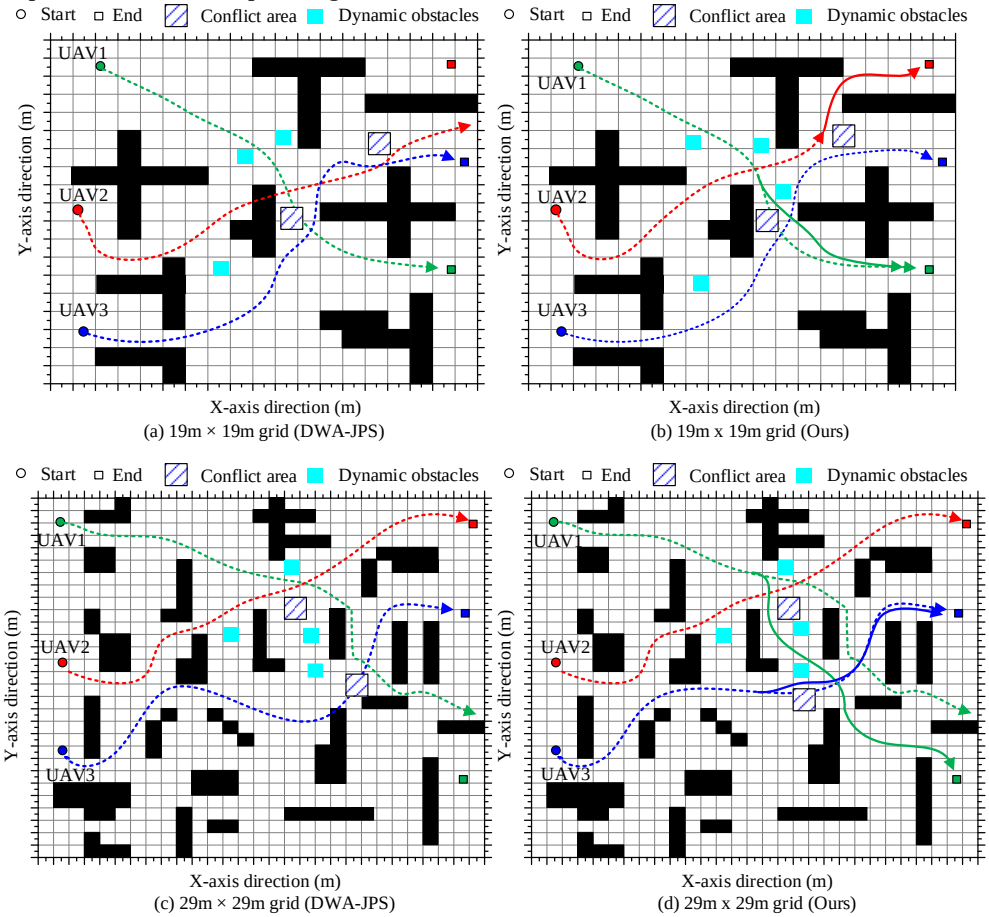


Fig. 12. PP test for 19m×19m and 29m×29m grid maps.

Fig. 12(a) and 12(b) show the planning results of DWA-JPS and Ours on a 19m×19m grid map. In the DWA-JPS PP, there was a clear conflict at the intersection of three UAVs, causing UAV 2 to avoid the right and fall into local convergence, unable to reach the target location smoothly. Meanwhile, the collision between UAV 1 and UAV 3 resulted in waiting and avoidance, leading to an extension of the planned distance. In Ours planning, the conflict avoidance strategy adopted by the research model in the conflict area was studied, and the route planning was re-conducted. There was no local convergence in the UAV 2 area, and the avoidance strategy also allowed the remaining UAVs to bypass the conflict in a shorter time and return to the predetermined planned trajectory. Fig. 12(c) and 12(d) show the planning results of DWA-JPS and Ours on a 29m×29m grid map. In DWA-JPS planning, UAV 1 still chose to avoid to the left at the conflict point, causing it to fall into local convergence and unable to return to the designated planned trajectory. The long waiting time of UAV 3 at the conflict point also affected the planning effectiveness. Ours adopted an avoidance strategy at the conflict point, predicting the conflict ahead and avoiding the wait for conflicts, thus preventing the problem of local convergence in planning, with the best overall performance. Next, three UAV road planning scenarios (10m×10m, 19m×19m, 29m×29m and 38m×38m) were selected for experiments to compare the average planning time of UAV groups with different technologies. The results are shown in Table II.

Table II shows the time-consuming comparison of road scenario planning for multi-UAV planning. Four planning scenarios were selected for comparison. Overall, Ours fleet planning was the best. For example, the average planning time of UAV 1 under four roads was 34.3s, while the average planning time of DWA-JPS was 39.0s. Especially in the more complex 38m×38m road planning, the average planning time of UAV 1, UAV 2 and UAV 3 in Ours was 34.3s, 34.2s and 34.0s, which was significantly better than 39.0s, 39.5s and 39.6s of DWA-JPS.

TABLE II COMPARISON OF AVERAGE PLANNING TIME OF UAV GROUP

| Planning road scenarios | DWA-JPS (s) | | | Ours (s) | | |
|---|---|---|---|---|---|---|
| | UAV1 | UAV2 | UAV3 | UAV1 | UAV2 | UAV3 |
| 10m×10m | 12.5 | 11.6 | 12.8 | 9.3 | 9.7 | 9.5 |
| 19m×19m | 21.6 | 22.5 | 23.5 | 17.6 | 17.8 | 16.8 |
| 29m×29m | 52.3 | 53.5 | 52.8 | 47.5 | 45.5 | 46.8 |
| 38m×38m | 69.5 | 70.5 | 69.2 | 62.8 | 63.8 | 62.8 |
| Average comprehensive time | 39.0 | 39.5 | 39.6 | 34.3 | 34.2 | 34.0 |

## IV. DISCUSSION AND CONCLUSION

With the swift advancement of UAV technology, multi-UAV collaborative PP has emerged as a study hotspot. To improve the effectiveness of multi-UAV PP, a multi-UAV PP technique based on an improved JPS algorithm was proposed and relevant experiments were conducted.

In single UAV PP, taking the 38m×38m grid map environment as an example, compared with A* and JPS algorithms, the proposed model improved the accuracy of X-axis control error by 7.25% and 9.28%, and had lower Y-axis control error. In static scene planning tests, the planning time was the shortest, and the PP length and number of extended nodes were better than the other two techniques. In dynamic obstacle planning scenarios, the proposed model could effectively predict the trajectory of dynamic obstacles, avoid waiting, and plan the shortest distance. The reason why the research technology was superior to traditional JPS and A* is that the introduction of geometric collision detection strategy improved the path search range. In addition, the introduction of DWA to predict the conflict range significantly improved the technical adaptability.

In terms of PP for multiple UAV swarms, the research was based on distributed control clusters and introduced UAV conflict avoidance strategies for planning. By setting collision fields and conflict avoidance rules, the problem of mutual collision among UAV swarms during collaborative operations was effectively solved. The experiment compared DWA-JPS with Ours, and the results showed that in the local conflict planning test, Ours could smoothly separate and return to its original trajectory, while DWA-JPS fell into local optima. In the multi-UAV planning test of 30m×30m grid map, Ours planning showed significantly lower number of expansion nodes, shorter planning time, and better average planning length. In the comparison of planning effects on grid maps of different sizes, Ours adopted a conflict avoidance strategy in conflict areas, avoiding local convergence and planning getting stuck in local optima, resulting in the best overall performance.

To sum up, the research technology performed well in the field of UAV planning, including: In the PP of single UAV, it significantly reduced the control error, shortened the length and time of PP, reduced the number of expansion nodes, and improved the effect of dynamic planning; In the multi UAV PP, the conflict between UAVs was effectively avoided, the local optimal problem was solved, the planning efficiency was improved, and the good cooperative operation ability was displayed. However, there are also shortcomings in the research technology, as it has not taken into account the influence of more dynamic objects in the air environment. In addition, more motion characteristics of UAVs have not been taken into account. In the future, it is necessary to fully consider the above issues and improve technological adaptability.

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# AHP and Fuzzy Evaluation Methods for Improving Cangzhou Honey Date Supplier Performance Management

Zhixin Wei*
Zhengzhou Shengda University, Zhengzhou 451191, Henan, China

***Abstract*—This study focuses on improving supplier performance management within the Cangzhou honey date industry by integrating the Analytic Hierarchy Process (AHP) and fuzzy evaluation methods. Recognizing the limitations of traditional evaluation systems—such as subjectivity and insufficient quantitative analysis—the research aims to build a comprehensive, data-driven evaluation framework. The methodology involves constructing a supplier performance index system based on five key dimensions: quality, cost, delivery, service, and social responsibility. Using the AHP method, expert opinions are quantified to determine the weight of each indicator. Subsequently, fuzzy evaluation is employed to transform qualitative judgments into numerical scores, enabling more objective assessment. Five major suppliers are evaluated empirically, and statistical methods such as ANOVA and cluster analysis are used to identify performance differences and classify suppliers into performance tiers. The results indicate that Supplier A excels in quality and service, Supplier B leads in delivery performance, while Suppliers C and E require significant improvements. Correlation analysis reveals strong links between supplier performance and key operational metrics such as product defect rates, procurement costs, and customer satisfaction. Based on these findings, the study proposes targeted improvement strategies including the adoption of Six Sigma practices, implementation of VMI and JIT models, and enhanced performance-based incentive mechanisms. The research confirms the effectiveness of combining AHP and fuzzy methods in supplier evaluation and provides actionable insights for improving supply chain efficiency, resilience, and competitiveness. It also suggests that future studies should incorporate larger datasets and intelligent algorithms to refine evaluation accuracy and operational decision-making.**

***Keyword*—AHP; fuzzy evaluation method; supplier performance; Cangzhou honey date; supply chain management***

## I. Introduction

With the rapid development of the market economy, the importance of supply chain management has become increasingly prominent in various industries [1]. Especially for agricultural products enterprises, the optimization of supplier performance management has become a key factor to enhance competitiveness and ensure product quality [2]. As an agricultural product with local characteristics, Cangzhou honey date is loved by consumers for its unique taste and rich nutritional value, and the market demand continues to grow. However, in the supply chain management of the honey date industry, there are still some management problems, including improper supplier selection, imperfect supplier performance evaluation system, and difficulty in stabilizing product quality. These problems directly affect the overall operational efficiency and market competitiveness of honey date enterprises. In the process of supplier management, how to scientifically and reasonably evaluate the performance of suppliers has become a challenge that enterprise managers must face [3]. Traditional performance evaluation methods mostly rely on qualitative analysis or a single quantitative index, which lacks comprehensiveness and systematicity. To solve this problem, the supplier performance evaluation system based on the hierarchical analysis method (AHP) and fuzzy evaluation method has gradually received attention from both academia and the business community. The AHP method can decompose the complex evaluation problem into multiple levels for quantitative analysis, while the fuzzy evaluation method can deal with the uncertainty and fuzzy information to make up for the shortcomings of the traditional evaluation methods [4]. The combined application of these two methods can more accurately assess the comprehensive performance of suppliers and provide powerful support for corporate decision-making [5]. The purpose of this paper is to construct a supplier performance management evaluation system applicable to the Cangzhou honey date industry by combining the AHP method and fuzzy evaluation method through empirical research [6]. The systematic analysis of the performance of multiple suppliers provides the theoretical basis and practical guidance for enterprises to optimize supplier management and improve the overall efficiency of the supply chain [7]. At the same time, this study also explores how to improve supplier performance management according to the evaluation results, so as to enhance the competitiveness and market share of honey date enterprises.

The structure of this study is as follows: Section II reviews the relevant research results in the field of supplier performance management, focuses on the theoretical basis, evaluation methods, and application status of supplier performance evaluation, and analyzes the application of AHP method and fuzzy evaluation method in supplier management. Section III describes in detail the construction method of the evaluation index system, the weight determination process of the AHP method, and the implementation steps of the fuzzy evaluation method adopted in this study. Section IV presents the performance evaluation results of Cangzhou honey date suppliers through empirical analysis, combines the evaluation data with an in- depth discussion of the advantages and

shortcomings of different suppliers, and puts forward relevant management improvement suggestions. Section V summarizes the main conclusions of this study, reviews the limitations of the study, and proposes directions for future research.

## II. Synthesis of Research

### A. Progress of Research on Supplier Performance Management

Supplier performance management is an important part of supply chain management, and its core objective is to select high-quality suppliers through a scientific evaluation system and continuously optimize supplier management to improve the overall operational efficiency of enterprises [8]. Existing research shows that supplier performance management involves multiple dimensions, including quality, cost, delivery capability, service level, and sustainability [9]. Traditional supplier evaluation methods mainly rely on expert experience or financial data analysis, but these methods have limitations in dealing with complex, multi-dimensional data [10]. In recent years, with the application of multi-criteria decision analysis (MCDM) methods, the supplier performance evaluation system has gradually developed towards systematization, quantification, and intelligence [11]. Fig. 1 illustrates the development of supplier performance evaluation methods and lists the main methods in chronological order, along with their characteristics and limitations.

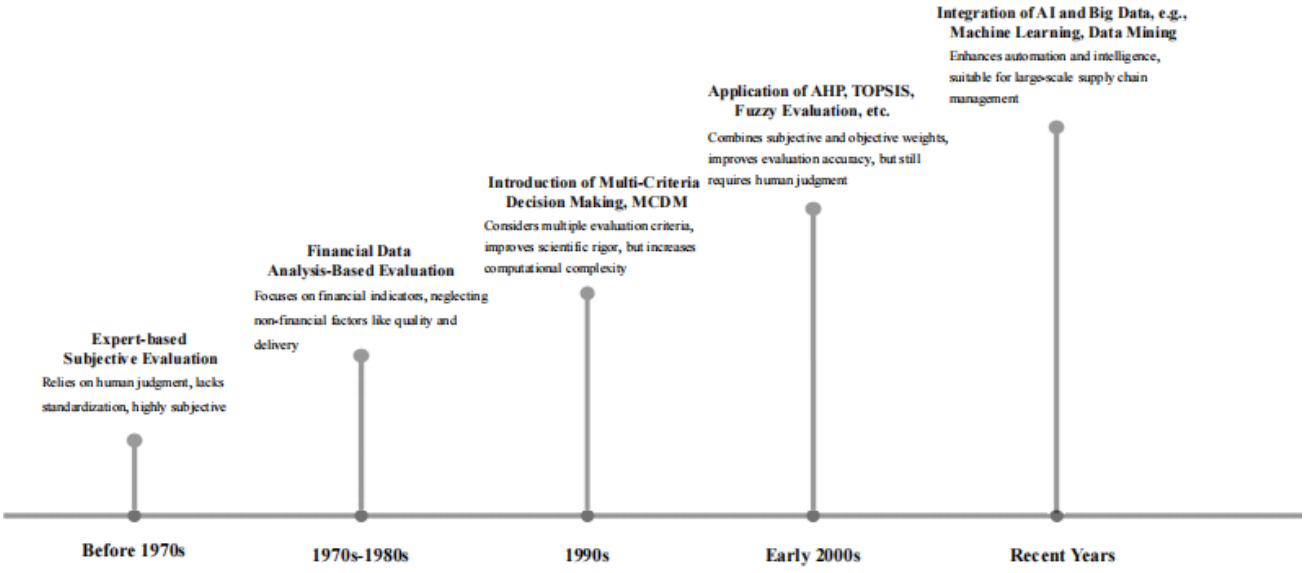


Fig. 1. Development of supplier performance evaluation methods.

### B. Application of AHP Method in Supplier Performance Evaluation

The hierarchical analysis method (AHP) is a decision analysis method proposed by Saaty in the 1970s, which is widely used in the field of supplier selection and performance evaluation [12]. The AHP method decomposes a complex decision problem into different levels of criteria by constructing a hierarchical structural model, constructs judgment matrices by using the expert scoring method, and ultimately calculates the weights of each index [13]. This method can effectively quantify expert judgment and improve the scientificity of the evaluation system. It has been shown that the application of the AHP method in the supply chain management of agricultural products has strong feasibility and can help enterprises assess the comprehensive ability of suppliers from multiple angles [14]. However, the AHP method has some limitations in dealing with ambiguity and uncertain information, especially in the expert scoring process, where subjective judgment may lead to biased evaluation results.

### C. Application of Fuzzy Evaluation Method in Supplier Management

The fuzzy evaluation method is a decision analysis method based on fuzzy mathematical principles, which is suitable for dealing with problems with high uncertainty [15]. In supplier performance management, many evaluation indexes are difficult to express by precise numerical values, such as "product quality stability" or "delivery reliability", which usually need to be evaluated by fuzzy linguistic variables (such as "excellent", "good", "fair"). The fuzzy evaluation method can transform expert opinions into fuzzy numbers and quantitatively analyze them through the affiliation function, thus reducing the influence of subjective factors and improving the reliability of evaluation results [16]. In recent years, the fuzzy evaluation method has been widely used in the supply chain of agricultural products, manufacturing, and retail industry supplier management as shown in Fig. 2.

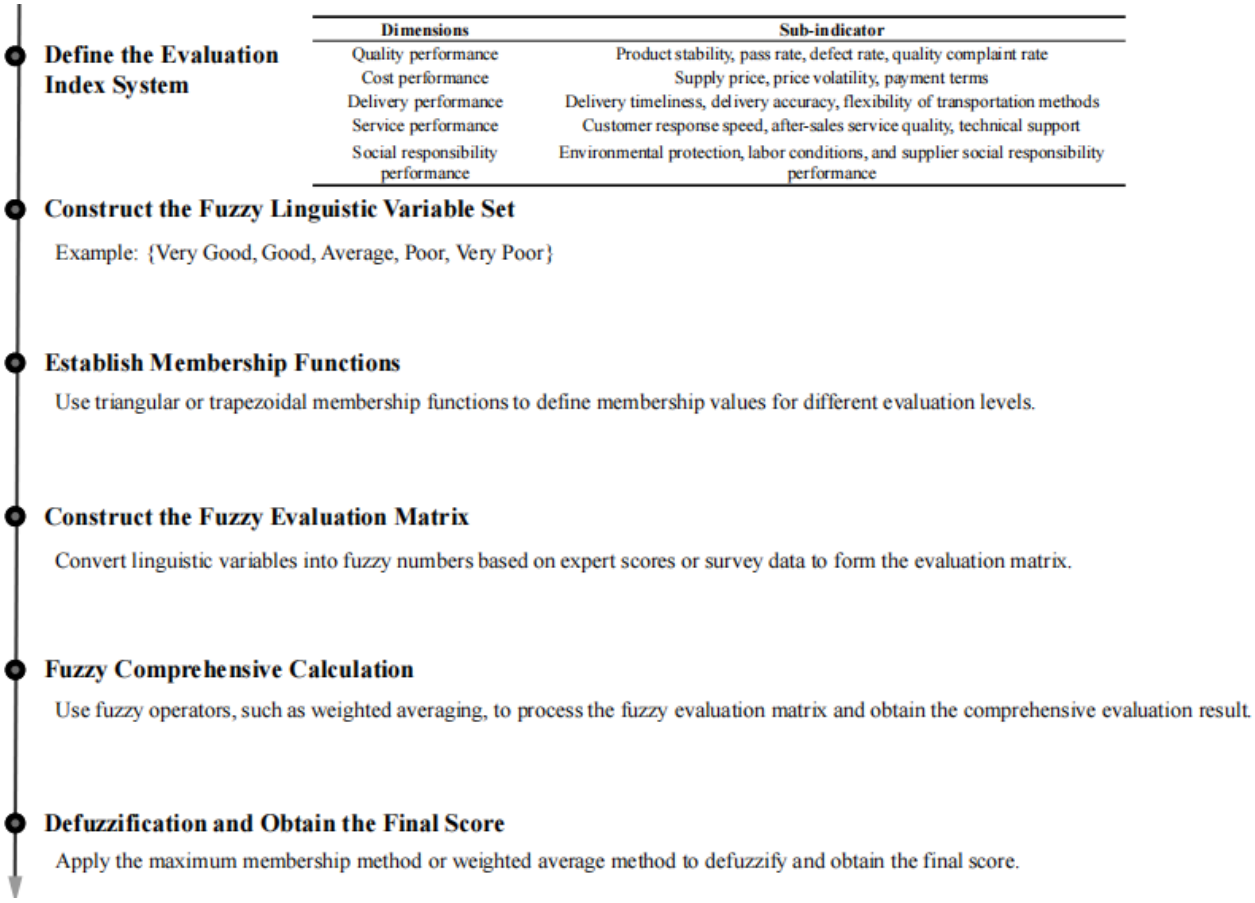


Fig. 2. Basic principle of the fuzzy evaluation method.

### *D. Combination of AHP and Fuzzy Evaluation Method and its Advantages*

To make up for the shortcomings of a single method, academics have proposed a combination of the AHP and fuzzy evaluation method, in which the AHP method is utilized to determine the weights of each evaluation index, and then the fuzzy evaluation method is used to provide a comprehensive score of the supplier's performance[17]. The main advantages of this method are:

- Clear hierarchical structure: The AHP method can effectively decompose complex problems and ensure the rationality of the evaluation index system.
- Reduction of subjective bias: the fuzzy evaluation method can quantify the fuzzy judgment of experts and improve the objectivity and accuracy of evaluation results.
- Applicable to the uncertain environment: especially in the agricultural supply chain, market demand fluctuates greatly, and supplier performance is affected by many uncertain factors, the combination of the AHP-fuzzy evaluation method can better deal with the complex environment.

It has been shown that the AHP-fuzzy evaluation method has been successfully applied in several fields, including manufacturing, the food supply chain, and the medical industry [18]. However, the current research on the supply chain of local speciality agricultural products is still relatively limited, especially for the Cangzhou honey date industry [19]. Therefore, this paper will build an evaluation system applicable to the performance management of Cangzhou honey date suppliers based on existing research, and verify its effectiveness through empirical analysis [20]. Fig. 3 below shows the combination process of AHP (hierarchical analysis method) and fuzzy evaluation method, especially the whole process from problem decomposition to final comprehensive evaluation.

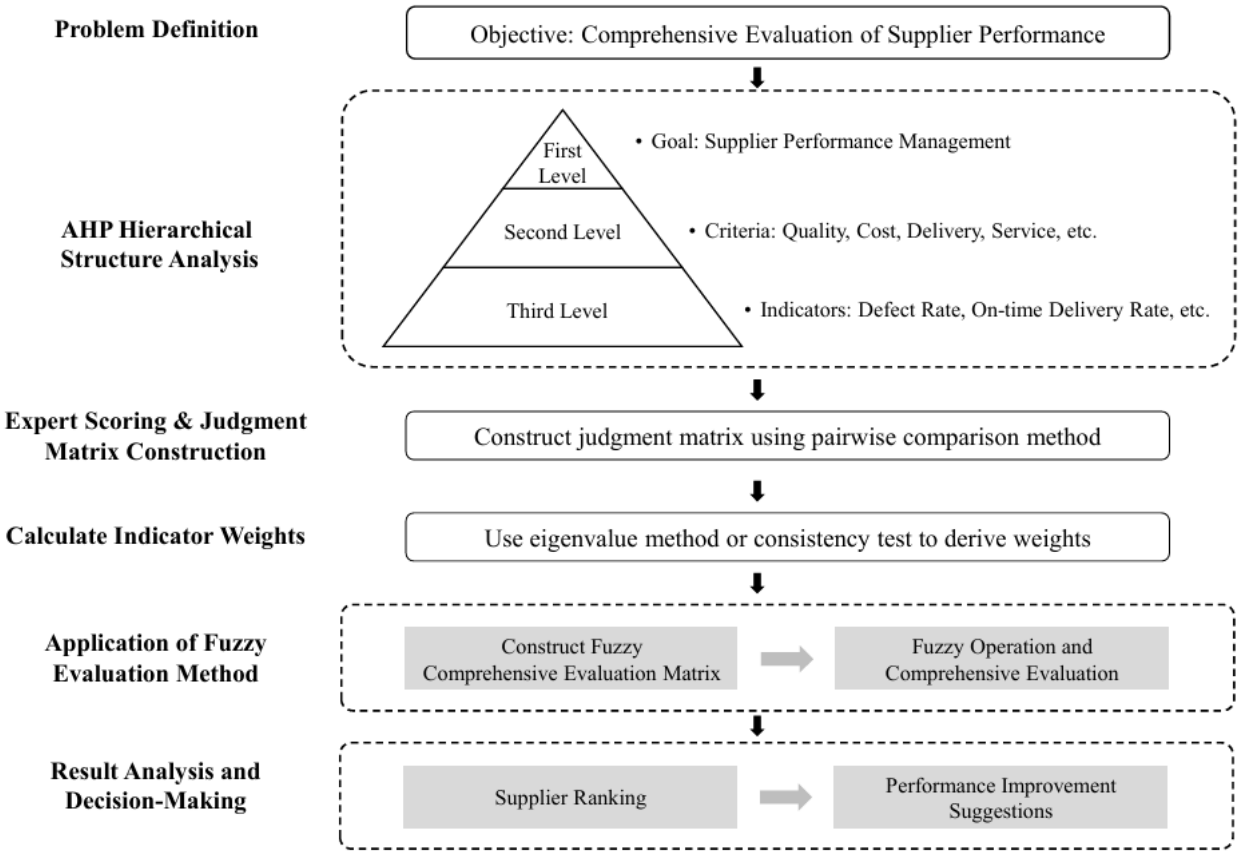


Fig. 3. Analytical framework diagram of the combined AHP-fuzzy evaluation method.

## III. Methodology

This study aims to construct a supplier performance management improvement system based on the hierarchical analysis method (AHP) and fuzzy evaluation method, focusing on the supplier performance evaluation of the Cangzhou honey date industry [21]. To achieve this goal, this study first carries out a detailed design of the construction process of the supplier performance evaluation system, and then empirically analyzes Cangzhou honey date suppliers using the AHP method and fuzzy evaluation method [22]. The research method mainly includes the following steps: constructing the evaluation index system, determining the weights of evaluation indexes, fuzzy processing supplier evaluation data, comprehensive evaluation, and result analysis.

### A. Construction of the Evaluation Indicator System

The core of supplier performance evaluation lies in the selection of appropriate evaluation indexes. Based on the characteristics of the Cangzhou honey date industry, combined with the classic theories of supply chain management and existing literature, this study constructs a supplier performance evaluation index system that includes five main dimensions, specifically: quality performance, cost performance, delivery performance, service performance and social responsibility performance [23]. Under each dimension, there are several sub-indicators, which can comprehensively reflect the supplier's comprehensive ability in different aspects [24]. The specific sub-indicators are shown in Table I. To ensure the scientificity and comprehensiveness of the evaluation index system, this study refers to several kinds of literature on supplier performance evaluation conducts interviews with several industry experts, and ultimately forms an evaluation framework applicable to the Cangzhou honey date industry.

TABLE I Supplier Performance Evaluation Indicator System

| Dimension (Math.) | Subindex |
|---|---|
| Quality performance | Product stability, pass rate, defect rate, quality complaint rate |
| Cost performance | Supply prices, price volatility, payment terms |
| Delivery performance | Timeliness of delivery, accuracy of delivery, flexibility of mode of transportation |
| Service performance | Customer responsiveness, after-sales service quality, technical support |
| Social responsibility performance | Environmental protection, labor conditions, fulfillment of suppliers' social responsibility |

### B. Determination of Weights of Evaluation Indicators

After determining the evaluation indicator system, the next step is to determine the weight of each evaluation indicator. Since the importance of each indicator varies in practical application, it is necessary to determine the weights of dimensions and sub-indicators by expert scoring method. In this study, the hierarchical analysis method (AHP) is used to determine the weights [25]. Fig. 4 shows in detail the hierarchical relationship of the AHP method in supplier performance evaluation, covering the target level (Top Level), criterion level (Criteria Level), and sub-criteria level (Sub-criteria Level) to reflect the hierarchical relationship of each evaluation factor. The following is a textual description of the steps of the AHP method: constructing a hierarchical model, expert judgment, constructing a judgment matrix, and calculating weights [26]. The specific process is as follows:

- Constructing a hierarchical model: Based on the research objectives and evaluation system, the overall objective (supplier performance evaluation) is first placed at the top level [27]. Then, five dimensions are taken as the factors in the second level, and each dimension is further subdivided into several sub-indicators under each dimension.
- Expert judgment and judgment matrix construction: through interviews with experts in the fields of supply chain management, procurement, quality management, etc., collect expert ratings on the relative importance of each dimension and sub-indicator [28]. The experts use a scale from 1 to 9 (e.g. 1 means that two factors are equally important, and 9 means that a factor is important).
- Calculation of weights: By constructing a judgment matrix and conducting consistency tests, the weights of each dimension and sub-indicator are finally calculated. The calculation methods of specific weights include the characteristic root method or the approximation method. To ensure the reasonableness of the calculation results, this study chose the weighted average method for data processing, and the results of the weights were strictly analyzed statistically [29]. After determining the index weights, we can quantitatively score the performance of each supplier in different dimensions.

### C. Application of the Fuzzy Evaluation Method

In the actual evaluation process, supplier performance is often affected by a variety of uncertainties, such as market fluctuations, supply chain disruptions, and other factors, which make some evaluation indexes difficult to express through precise numerical values [30]. To deal with these uncertainties, this study adopts the fuzzy evaluation method to further process the scoring results obtained by the AHP method [31]. The main steps of the fuzzy evaluation method include:

- Fuzzy scoring: Since experts often use fuzzy language, such as "excellent", "good", "fair", "poor", etc., when evaluating supplier performance, this study translates linguistic evaluations into corresponding fuzzy numbers. The fuzzy number of each evaluation index can be expressed by a triangular fuzzy number or trapezoidal fuzzy number, for example, the corresponding fuzzy number of "excellent" is (8, 9, 9), which means that experts believe that the supplier's performance in this index is extremely excellent.
- Establishment of affiliation function: The key to the fuzzy evaluation method is how to convert the fuzzy numbers into specific affiliation values [32]. By constructing an affiliation function suitable for this study, the fuzzy scores can be converted into specific values, which makes it possible to further compare the performance scores of suppliers.
- Weighted Fuzzy Comprehensive Evaluation: The weights determined by the AHP method are combined with the fuzzy scores, and the final supplier performance score is calculated through the weighted average method. In this way, the problem of uncertainty that cannot be handled in the traditional scoring method can be effectively solved. In the process of fuzzy evaluation, the weights of the dimensions and sub-indicators are combined to finally arrive at the comprehensive performance score of each supplier as shown in Table II.

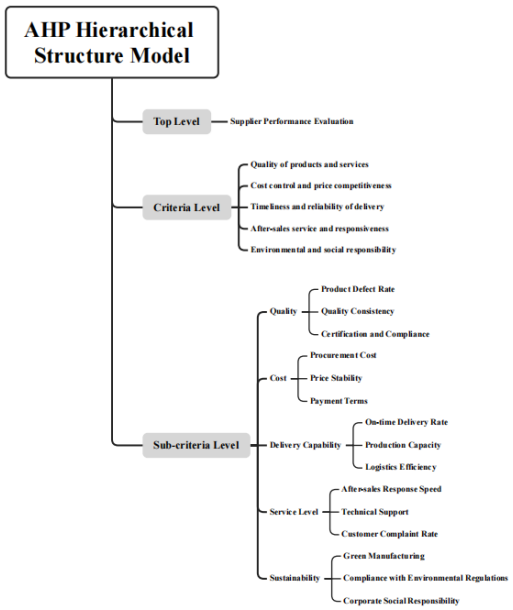


Fig. 4. Hierarchy diagram of the AHP method.

TABLE II EXAMPLE OF FUZZY EVALUATION MATRIX

| Provider | Quality performance | Cost performance | Delivery performance | Service performance | Social responsibility performance |
|---|---|---|---|---|---|
| Supplier A | (8, 9, 9) | (7, 8, 9) | (6, 7, 8) | (7, 8, 8) | (6, 7, 8) |
| Supplier B | (7, 8, 9) | (6, 7, 8) | (7, 8, 9) | (6, 7, 8) | (7, 8, 9) |

### D. Data Collection and Analysis

To ensure the scientificity and reliability of the study, five major suppliers in the Cangzhou honey date industry were selected as samples for this study, covering suppliers of different sizes and geographic regions. The performance data of these suppliers come from public industry reports, enterprise interviews, and expert ratings [33]. By scoring each supplier's indicators and combining the expert's weighting judgment, this study has come up with comprehensive evaluation results of the suppliers [34]. The data analysis process was carried out using SPSS and Excel to ensure the statistical soundness of the data, and a series of reliability and validity tests were conducted to ensure the validity of the final evaluation results.

### E. Analysis of Results and Improvement Measures

The performance scores of each supplier obtained through AHP and the fuzzy evaluation method will provide a scientific basis for the supplier management of the Cangzhou honey date industry. Combined with the resulting supplier performance scores, enterprises can formulate improvement measures for poorly performing suppliers to further optimize supply chain management. At the same time, this study will also provide enterprises with a supplier performance management improvement framework based on AHP and fuzzy evaluation method, which will help enterprises to effectively improve the level of supplier management in actual operation.

## IV. Results and Discussion

### A. Results of Supplier Performance Evaluation

Based on the evaluation system and analysis method established in the previous section, this study used the hierarchical analysis method (AHP) to determine the weights of each evaluation dimension and combined it with the fuzzy evaluation method to score the performance of five major suppliers. The performance scores of each supplier are analyzed in detail below.

*1) Statistical analysis of supplier performance scores*: To ensure the robustness and reliability of the supplier performance evaluation results, this study statistically analyzed the obtained rating data. The mean, standard deviation, and coefficient of variation of each supplier on different performance dimensions were calculated to measure the stability and consistency of each supplier's performance [35]. Suppliers with lower standard deviations indicate more consistent performance, while suppliers with higher standard deviations may need further optimization. In addition, this study conducted an analysis of variance (ANOVA) on the performance scores of each supplier to test whether there is a significant difference in the scores of different suppliers on each performance dimension [36]. When the significance level (p- value) is less than 0.05, it indicates that at least one supplier's performance is statistically significantly different from other suppliers. For significant differences, the Tukey HSD post hoc test was further used in this study to clarify the comparative results between suppliers where the specific differences lie.

TABLE III Descriptive Statistics and ANOVA Results for Supplier Performance Scores

| Performance dimensions | Provider | Mean | Standard Deviation (SD) | Coefficient of variation (CV) | F-value | p-value | Significant difference (Tukey HSD) |
|---|---|---|---|---|---|---|---|
| **Quality performance** | A | 8.5 | 0.42 | 4.94% | 6.87 | 0.002 | A > C, E |
| | B | 7.9 | 0.51 | 6.46% | | | |
| | C | 6.8 | 0.65 | 9.56% | | | |
| | D | 7.7 | 0.49 | 6.36% | | | |
| | E | 6.5 | 0.72 | 11.08% | | | |
| **Cost performance** | A | 7.2 | 0.55 | 7.64% | 3.92 | 0.027 | No significant difference |
| | B | 7.5 | 0.47 | 6.27% | | | |
| | C | 6.9 | 0.61 | 8.84% | | | |
| | D | 7 | 0.52 | 7.43% | | | |
| | E | 6.7 | 0.66 | 9.85% | | | |
| **Delivery performance** | A | 8.2 | 0.4 | 4.88% | 9.25 | <0.001 | B > C, D, E |
| | B | 8.6 | 0.35 | 4.07% | | | |
| | C | 7.1 | 0.6 | 8.45% | | | |
| | D | 7.3 | 0.58 | 7.95% | | | |
| | E | 6.8 | 0.67 | 9.85% | | | |
| **Service performance** | A | 8.3 | 0.38 | 4.58% | 7.88 | 0.001 | A > C, E |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | B | 7.8 | 0.49 | 6.28% | | | |
| | C | 6.9 | 0.57 | 8.26% | | | |
| | D | 7.5 | 0.5 | 6.67% | | | |
| | E | 6.6 | 0.71 | 10.76% | | | |
| **Social responsibility** | A | 7.9 | 0.47 | 5.95% | 4.63 | 0.013 | No significant difference |
| | B | 7.6 | 0.5 | 6.58% | | | |
| | C | 7 | 0.59 | 8.43% | | | |
| | D | 7.8 | 0.48 | 6.15% | | | |
| | E | 6.9 | 0.63 | 9.13% | | | |
| **Consolidated performance** | A | 8.1 | 0.4 | 4.94% | 8.76 | <0.001 | A > C, E |
| | B | 7.8 | 0.45 | 5.77% | | | |
| | C | 7 | 0.58 | 8.29% | | | |
| | D | 7.5 | 0.52 | 6.93% | | | |
| | E | 6.7 | 0.69 | 10.30% | | | |

As can be seen in Table III, Supplier A excels in most of the performance dimensions, with the highest or near-highest means in Quality Performance, Delivery Performance, and Service Performance, and a small standard deviation, which suggests that its performance is relatively stable. Supplier B has the highest score in Delivery Performance (mean 8.6), indicating a significant advantage in On-Time Delivery and Supply Chain Management. In contrast, Supplier C and Supplier E have low scores in several dimensions, especially in quality performance and delivery performance, with large standard deviations, indicating that their performance is less stable and there is more room for improvement. The results of the analysis of variance (ANOVA) showed that there were significant differences ($p < 0.05$) among different suppliers on the quality, delivery, service, and overall performance dimensions. Among them, the highest F-value ($F = 9.25$, $p < 0.001$) was found in the delivery performance dimension, indicating that the most significant differences between suppliers were found in delivery capability. Tukey HSD post hoc tests further showed that both supplier A and supplier B were significantly better than suppliers C and E in quality, delivery, and service performance, while in the cost performance and social responsibility performance dimensions, no significant differences were found between suppliers did not show any significant difference between them ($p > 0.05$). The results further validate the variability of suppliers in different performance dimensions and provide a quantitative basis for supplier performance management [37]. Enterprises can optimize their supplier selection strategy accordingly, focusing on strengthening the management and support of suppliers C and E. Meanwhile, suppliers A and B are encouraged to further improve their performance based on their existing strengths to promote the overall optimization of the supply chain.

*2) Cluster analysis of supplier performance*: To further explore the similarities and differences among suppliers, this study uses a systematic cluster analysis approach to categorize suppliers based on their performance scores. The results of cluster analysis can identify suppliers with similar characteristics and provide deep insights into their strengths and weaknesses [38]. In this study, Euclidean distance was used as the similarity measure, and Ward's minimum variance method was used as the clustering algorithm to ensure the rationality of the classification. Finally, the suppliers were categorized into three categories: "High-performing suppliers", "Medium- performing suppliers", and "Low-performing suppliers". High-performing suppliers excel in several dimensions, while low-performing suppliers score low in several dimensions. Fig. 5 below shows a clustered dendrogram of supplier performance, demonstrating the similarity of relationships between different suppliers [39]. The figure shows that suppliers A and B are first clustered into one category, indicating that they are very similar in terms of performance. Suppliers C and E are also clustered into one category, showing that they are similar in performance. Supplier D is clustered in a separate category, indicating that its performance is quite different from the other suppliers.

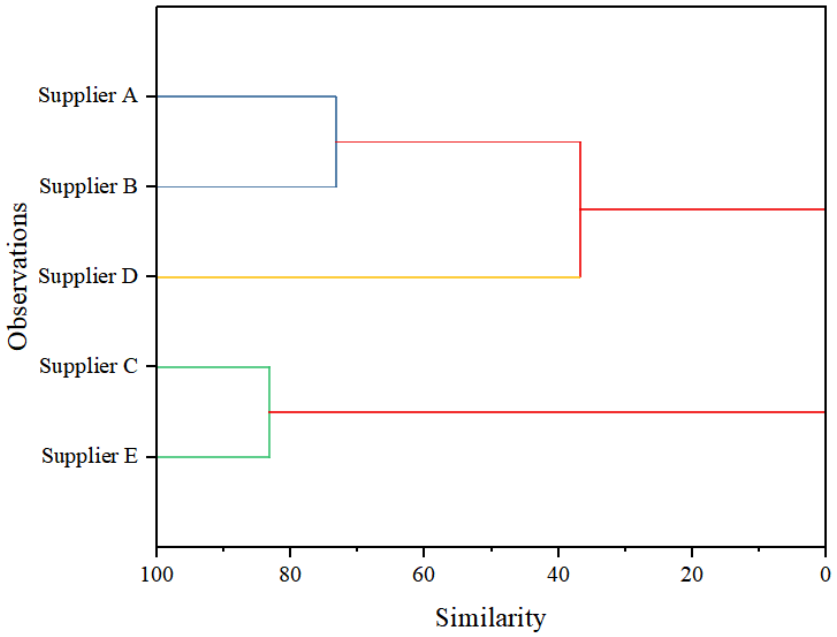


Fig. 5. Tree diagram of supplier performance clustering.

## B. Discussion of Results

*1) Trend analysis of performance scores*: This study further analyzes the time series of suppliers' performance scores, and Fig. 6 below exhibits a time series line graph of suppliers' performance scores to examine the trend of their performance changes over the ten evaluation cycles. The line graphs are used to show the changes in the scores of different suppliers in each dimension to determine whether the performance of suppliers shows a steady upward or downward trend [40]. The analysis results show that the overall performance scores of Supplier A and Supplier B show an upward trend over time, indicating continuous optimization in quality control, delivery capability, and service level. The performance scores of Supplier C and Supplier E are more volatile, indicating possible instability in their production and logistics management.

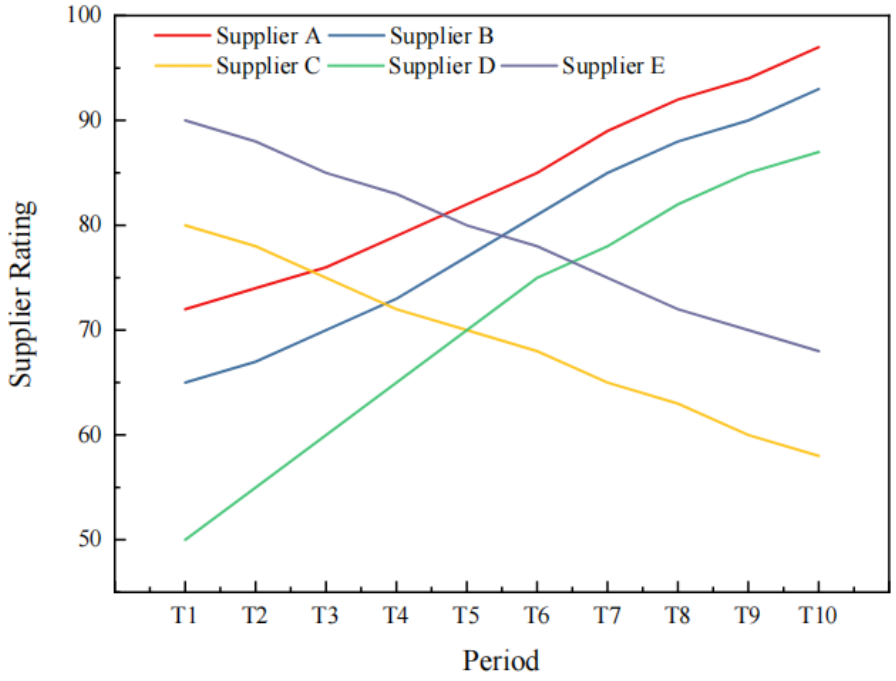


Fig. 6. Time-series line graph of supplier performance ratings.

*2) Impact of supplier performance on business operations*: Supplier performance has a direct impact on the production efficiency, cost control, and customer satisfaction of an enterprise. In this study, Pearson correlation analysis was used to measure the correlation coefficients between suppliers' performance dimensions and the key operation indexes of the enterprise, and the specific data. From Table IV, the analysis results show that there are various significant correlations between suppliers' performance dimensions and the operation indexes of the enterprise. Among them, quality performance has a significant negative correlation with product defect rate ($r$ = -0.82, $p < 0.01$), which indicates that suppliers' excellent performance in quality control can effectively reduce the defect rate of the enterprise's products and thus improve the overall production efficiency ($r = 0.80$, $p < 0.01$). In addition, delivery performance is significantly positively correlated with on-time order fulfillment ($r = 0.76$, $p < 0.05$), suggesting that suppliers' delivery capability directly affects on-time order fulfillment, which in turn affects firms' supply chain stability. In terms of cost control, cost performance is negatively correlated with overall purchasing cost ($r$ = -0.69, $p < 0.05$), suggesting that suppliers with good cost management capabilities help to reduce firms' purchasing costs. However, the correlation between cost performance and other operational indicators (e.g., productivity and customer satisfaction) is not significant, which may imply that a low-cost strategy does not necessarily directly improve a firm's operational efficiency [41]. In contrast, service performance had the highest correlation with customer satisfaction ($r = 0.81$, $p < 0.01$), reflecting that suppliers' service quality has a key impact on customer experience and also contributes positively to production efficiency ($r = 0.70$, $p < 0.01$). In addition, social responsibility performance is positively correlated with customer satisfaction ($r = 0.67$, $p < 0.05$) and productivity ($r = 0.55$, $p > 0.05$), but the correlation is relatively low, suggesting that despite the impact of social responsibility factors in terms of corporate image and sustainability, they have a limited role to play in the short-term improvement of operational efficiency.

TABLE IV CORRELATION MATRIX OF SUPPLIER PERFORMANCE DIMENSIONS WITH BUSINESS OPERATING INDICATORS

| Performance Dimensions | Product Defect Rate | Orders on Time Compliance Rate | Overall Procurement Costs | Customer Satisfaction | Production Efficiency |
|---|---|---|---|---|---|
| Quality performance | -0.82** | 0.64* | -0.45 | 0.78** | 0.80** |
| Delivery performance | -0.59* | 0.76* | -0.38 | 0.72** | 0.68* |
| Cost performance | 0.40 | -0.35 | -0.69* | -0.42 | -0.37 |
| Service performance | -0.50 | 0.58* | -0.32 | 0.81** | 0.70** |
| Social responsibility | -0.36 | 0.42 | -0.27 | 0.67* | 0.55 |

Note: * $p < 0.05$, ** $p < 0.01$, Negative correlation coefficients indicate the inhibitory effect of the performance dimension on the operational indicators, and positive correlation coefficients indicate the facilitating effect.

### C. Recommendations for Improvement in Performance Management

This study draws on the supplier management practices of leading international companies to explore feasible performance optimization strategies. Table V shows the comparison between the supplier management strategies of leading enterprises and those of this study. In terms of quality management systems, leading enterprises such as Toyota enhance product consistency through data-driven methods such as Six Sigma, while this study's enterprises mainly rely on self- inspection by suppliers and lack a systematic quality optimization mechanism, which suggests that there is still room for improvement in their quality management approach. In terms of supply chain coordination mechanism, Apple and other enterprises adopt Vendor Managed Inventory (VMI) and Just-In-Time (JIT) models to make the supply chain response more efficient, whereas this research enterprise still carries out inventory management in the traditional way, which leads to a lower degree of supply chain coordination and higher inventory costs. In addition, in terms of supplier incentives, leading companies such as Bosch have established a performance- based long-term cooperation mechanism to ensure that high-quality suppliers get long-term cooperation opportunities, while the supplier performance evaluation mechanism of this research enterprise is not perfect and the incentive is insufficient, making it difficult to fully mobilize the enthusiasm of suppliers [42]. In terms of technology and innovation support, enterprises such as Siemens improve the technology level of the overall supply chain through joint research and development of innovation projects with suppliers, while the suppliers of this research enterprise have weak innovation capabilities. Finally, in terms of sustainability and social responsibility, enterprises such as Starbucks have set up strict ethical sourcing standards for their suppliers, while this study's enterprises are more lax in assessing the social responsibility of their suppliers and have not yet established specific evaluation criteria [42]. This study proposes the following optimization suggestions in conjunction with the case study: introducing Six Sigma management methodology to improve product consistency through data-driven quality optimization strategies to strengthen the supplier quality management system; adopting the VMI and JIT models to improve supply chain responsiveness and reduce inventory costs in order to optimize the supply chain synergy mechanism; At the same time, strengthen the supplier incentive mechanism, the establishment of performance-based supplier rating and incentive mechanism, to ensure that high-quality suppliers to obtain long-term cooperation opportunities, to enhance the overall supplier quality level.

TABLE V COMPARISON OF SUPPLIER MANAGEMENT STRATEGIES OF LEADING COMPANIES AND COMPANIES IN THIS STUDY

| Supply Chain Management Strategy | Leading Enterprise Practices | Current status of this research enterprise | Gap analysis |
|---|---|---|---|
| Quality Management System | Toyota Adopts Six Sigma for Data-Driven Quality Optimization | Quality management relies heavily on supplier led self-inspection and lacks data analysis | Lack of systematic quality management system, need to introduce data analysis tools |
| Supply chain synergies | Apple Applies VMI and JIT Models to Optimize Supply Chain | Supplier inventory management is more traditional and supply chain synergy is low | Lower supply chain integration and higher inventory costs |
| Supplier incentives | Bosch adopts performance-based long-term cooperation mechanisms | Inadequate supplier performance appraisal mechanisms and insufficient incentives | Lack of systematic assessment and incentives, insufficient motivation of suppliers |
| Technology and innovation support | Siemens develops joint innovation programs with suppliers | Weak supplier innovation and less collaborative R&D | Insufficient supplier innovation support to drive long-term improvements |
| Sustainable development and social responsibility | Starbucks sets ethical sourcing standards for suppliers | Social responsibility assessment is more lenient and no specific criteria have been set | Supplier social responsibility assessment system has not yet been established |

## V. CONCLUSION

Based on the AHP and fuzzy evaluation method, this study constructs an evaluation system for supplier performance management of Cangzhou honey dates, systematically evaluates the performance of major suppliers, and proposes corresponding improvement strategies. The results of the study show that Supplier A has the best performance in quality and service performance, Supplier B has obvious advantages in delivery performance, while Supplier C and Supplier E have relatively low scores in several dimensions, and there is a large room for improvement. Supplier D is more balanced in terms of quality and social responsibility performance, but there is still room for optimization in terms of cost control and delivery stability. Overall, the performance management system constructed in this study can provide empirical support for supplier selection and management in the Cangzhou honey date industry, which helps enterprises make scientific supply chain decisions in actual operation and improves the efficiency and stability of the overall supply chain. The study further shows that the combination of AHP and fuzzy evaluation method has strong applicability in supplier performance evaluation, which can synthesize multi-dimensional performance indicators and provide more comprehensive and accurate evaluation results for enterprises. In addition, the study reveals the relationship between supplier performance and key indicators of enterprise operation through correlation analysis, which further verifies the important impact of supplier quality, delivery capability, and cost control on enterprise supply chain performance. These findings not only provide a theoretical basis for the supplier management of the Cangzhou honey date industry but also provide valuable reference for the supply chain management of other agricultural products. Based on the performance evaluation results, this paper puts forward the following management improvement suggestions: optimize the supplier evaluation and selection mechanism, establish a dynamic evaluation system, combined with data monitoring and real- time feedback, to improve the timeliness of performance evaluation; strengthen the supply chain collaborative management, enhance the information sharing and collaborative operation efficiency between the enterprise and the supplier, in order to reduce the delivery risk and the inventory cost; introduce the performance incentive mechanism, and through the contract incentive, Long-term cooperation mechanism, etc., to improve the service quality and delivery capability of suppliers; strengthen the management of supplier social responsibility, and promote the improvement of suppliers in sustainable development, environmental protection and labor rights and interests, so as to enhance the sustainable competitiveness of the overall supply chain.

Although this study has achieved certain results, there are still some limitations. First, this study only analyzes the data based on five suppliers, and the sample size is relatively small. Future studies can further expand the sample scope and introduce more different types of suppliers for comparative analysis to improve the generalizability of the findings. Second, this study mainly adopts AHP and fuzzy evaluation methods for supplier performance assessment, although these two methods can effectively synthesize qualitative and quantitative factors, there may be some computational complexity limitations when dealing with large-scale supply chain data. Future research can combine machine learning, data mining, and other intelligent analysis techniques to improve the automation level and accuracy of supplier performance assessment. In addition, future research can further explore the in-depth integration of supplier performance evaluation with supply chain risk management, supplier cooperation mechanism, etc., to build a more complete supply chain optimization strategy and provide enterprises with more practical value of decision support. The conclusions of this study are not only applicable to the supplier management of the Cangzhou honey date industry but also can provide theoretical guidance and practical references for other agricultural supply chains and even the broader manufacturing and retail industries. In the future, with the development of digitalization and intelligence in supply chain management, supplier performance management methods will also be further innovated and optimized to adapt to the complex and changing market environment.

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# Air Quality Assessment Based on CNN-Transformer Hybrid Architecture

Yuchen Zhang, Rajermani Thinakaran
Faculty of Data Science and Information Technology, INTI International University, Malaysia

***Abstract*—Air quality assessment plays a crucial role in environmental governance and public health decision-making. Traditional assessment methods have limitations in handling multi-source heterogeneous data and complex nonlinear relationships. This paper proposes an air quality assessment model based on a CNN-Transformer hybrid architecture, which achieves end-to-end prediction by integrating CNN's local feature extraction capability with Transformer's advantage in modeling global dependencies. The model employs a three-layer CNN for local feature learning, combined with Transformer's multi-head self-attention mechanism to capture long-range dependencies, and uses multilayer perceptrons for final prediction. Experiments on public datasets demonstrate that compared to traditional machine learning methods and single deep learning models, the proposed hybrid architecture achieves a 10.2 percentage improvement in Root Mean Square Error (RMSE) and a 0.57 percentage point improvement in coefficient of determination ($R^2$). Through systematic ablation experiments, we verify the necessity of each model component, particularly the importance of the CNN-Transformer hybrid architecture, positional encoding mechanism, and multi-layer network structure in enhancing prediction performance. The research results provide an effective deep learning solution for air quality assessment.**

***Keywords*—Air quality assessment; deep learning; CNN-Transformer hybrid architecture; feature extraction**

## I. INTRODUCTION

In recent years, with the acceleration of industrialization and urbanization, air pollution has become increasingly severe, emerging as a critical environmental issue affecting human health and sustainable social development [1]. Air pollution shows significant correlation with the incidence of various diseases, including respiratory and cardiovascular diseases, and has become a focal point in global public health [2]. Particularly in rapidly developing urban areas, the overlapping effects of multiple pollution sources, including industrial activities, vehicle exhaust emissions, and construction work, have led to increasingly complex air quality issues. Accurate assessment and prediction of air quality not only provide crucial guidance for public health decision-making but also offer necessary scientific basis for pollution prevention and environmental governance. Meanwhile, precise air quality assessment holds significant value for formulating environmental protection policies, optimizing urban planning, and improving public quality of life.

Traditional air quality assessment methods primarily rely on expert experience and statistical models [3]. While these methods have certain practicality based on limited monitoring data and simplified mathematical models, they show obvious limitations in handling multi-source heterogeneous data and capturing complex nonlinear relationships. Particularly in real-world scenarios with variable weather conditions and complex pollution sources, traditional methods struggle to accurately characterize the spatiotemporal evolution patterns of air quality. With the rapid development of deep learning technology, air quality assessment methods based on deep neural networks have demonstrated powerful modeling capabilities and prediction potential [4]. Deep learning methods can automatically learn feature representations from large-scale data, showing significant advantages in handling high-dimensional nonlinear problems.

Currently, domestic and international scholars have conducted extensive research in the field of air quality assessment. Early research mainly adopted statistical regression methods, such as multiple linear regression and support vector regression, which offer high computational efficiency but limited model expressiveness [3]. These methods typically assume simple linear relationships between features, making it difficult to capture the complex spatiotemporal dependencies and multi-scale characteristics in air quality data. Subsequently, researchers began experimenting with deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), significantly improving prediction accuracy [4]. CNNs excel in feature extraction capability, effectively processing local patterns in air quality data, while RNNs capture temporal dependencies through their recurrent structure. However, these methods still face challenges in handling long-distance feature dependencies.

Recently, the Transformer architecture has achieved breakthrough progress in multiple fields including natural language processing and computer vision [5], with its multi-head self-attention mechanism effectively modeling long-distance dependencies in sequence data. However, in tasks involving multi-scale feature fusion like air quality assessment, relying solely on the Transformer structure makes it difficult to fully utilize the local structural information in the data [6]. Meanwhile, air quality data exhibits obvious spatiotemporal correlation, influenced by complex factors including meteorological conditions, geographical environment, and human activities, making it challenging for traditional deep learning models to effectively model both local and global features [7]. Additionally, air quality data often faces quality issues such as noise, missing values, and anomalies, making it important to improve model robustness and generalization ability.

Based on the above analysis, this paper proposes an air

quality assessment model based on a CNN-Transformer hybrid architecture. Through integrating CNN's advantages in local feature extraction and Transformer's capability in capturing long-range dependencies, this model constructs an end-to-end prediction framework. This hybrid architecture not only effectively handles multi-scale features in air quality data but also demonstrates strong robustness when facing noise and anomalies. Specifically, the main contributions of this paper include:

- Design of a novel hybrid deep learning architecture that effectively integrates CNN's local perception capability and Transformer's global modeling ability, achieving adaptive fusion of multi-scale features. This architecture captures spatiotemporal dependencies at different scales through hierarchical feature extraction and attention mechanisms.
- Proposal of a systematic data preprocessing and feature engineering method that improves model prediction stability through feature correlation analysis and composite feature construction. Specialized data cleaning and anomaly detection strategies are designed based on the characteristics of air quality data.
- Verification of the effectiveness of the proposed method and the necessity of each component through extensive comparative experiments and ablation studies, providing new solutions for air quality assessment tasks. Experimental results show that this hybrid architecture outperforms existing methods across multiple evaluation metrics.

## II. Related Works

Air quality assessment methods have evolved from traditional statistical methods to machine learning, and then to deep learning methods. This chapter systematically reviews and analyzes the key research work in this field.

In the context of the big data era, air quality assessment methods have achieved significant progress. Zheng et al. [8] first proposed U-air, a big data-based urban air quality inference framework that comprehensively considered air quality, meteorological data, and multiple urban factors to establish a scalable prediction model. Subsequently, Lyu et al. [9] proposed a bias correction framework for PM2.5 prediction, significantly improving model prediction accuracy in China. While these early works laid important foundations for subsequent research, they still had limitations in handling complex nonlinear relationships.

With the development of deep learning technology, air quality assessment methods based on deep neural networks have demonstrated powerful modeling capabilities. Freeman et al. [10] pioneered the application of deep learning to air quality time series prediction, demonstrating through comparative experiments the significant advantages of deep learning methods over traditional approaches. Qi et al. [11] proposed the Deep Air Learning framework, innovatively achieving air quality data interpolation, prediction, and feature analysis, making breakthrough progress in processing fine-grained air quality data. Zhang et al. [12] designed a specialized deep learning architecture for air quality prediction, enhancing model performance through multi-level feature extraction.

Recently, research focus has gradually shifted towards spatiotemporal sequence modeling and knowledge transfer. Wei et al. [13] explored the possibility of inter-city knowledge transfer, proposing a cross-city air quality prediction method that effectively addressed the data sparsity problem. Lin et al. [14] enhanced prediction accuracy by mining spatiotemporal patterns, with their proposed deep learning framework effectively capturing the spatiotemporal characteristics of pollutant dispersion. Wen et al. [15] further proposed a spatiotemporal convolutional long short-term memory neural network, achieving state-of-the-art performance in pollutant concentration prediction tasks.

However, existing research still has several limitations: First, most methods focus on single-scale feature extraction, making it difficult to simultaneously process local and global features; Second, the model's capability in fusing multi-source heterogeneous data needs improvement; furthermore, prediction performance under extreme weather conditions still requires enhancement. Based on the analysis of existing research, this paper proposes a novel CNN-Transformer hybrid architecture, aiming to overcome these limitations and provide more accurate and reliable air quality assessment methods.

## III. Methodology

As shown in Fig. 1, this study proposes an air quality assessment model based on a CNN-Transformer hybrid architecture. The model constructs an end-to-end regression prediction framework by integrating CNN's advantages in local feature extraction with Transformer's capability in capturing long-range dependencies. The model input includes nine environmental feature parameters: temperature, humidity, PM2.5, PM10, NO2, SO2, CO, proximity to industrial areas, and population density. To enhance model robustness, input data first undergoes standardization to eliminate scale differences between different features [16].

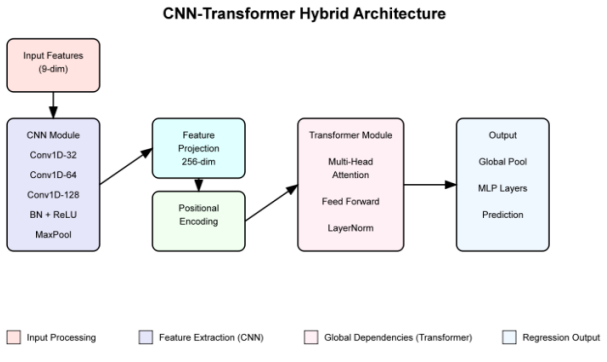


Fig. 1. Architecture of CNN-Transformer hybrid model for air quality assessment.

In the feature extraction phase, the model first employs a three-layer CNN structure for local feature learning. Each

CNN layer consists of one-dimensional convolution operations, batch normalization, ReLU activation function, and max pooling layer. The mathematical expression for one-dimensional convolution is Formula (1):

$$F_{out}(i) = \sum_{k=1}^{K} w_k \cdot F_{in}(i + k - \frac{K+1}{2}) + b \quad (1)$$

where, $F_{in}$ and $F_{out}$ represent input and output features respectively, $w_k$ denotes convolution kernel weights, K is the kernel size, and $b$ is the bias term. Through progressively increasing channel numbers (32 to 64 to 128), the model can extract multi-scale local pattern features. The batch normalization operation after each convolution layer can mitigate internal covariate shift problems and improve training stability. The max pooling layer preserves significant features through dimensionality reduction while reducing computational complexity.

After feature extraction, the model uses a linear projection layer to map CNN output to a fixed dimension (256 dimensions) and adds positional encoding to preserve sequence information. Positional encoding is generated using sinusoidal functions, ensuring the model can perceive relative position relationships between features. Subsequently, features are input into the Transformer encoder for global dependency modeling. The multi-head self-attention mechanism in Transformer can be expressed as Formula (2):

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (2)$$

where, Q, K, V represent query, key, and value matrices respectively, and $d_k$ is the dimension of the key vectors. By computing 8 different attention heads in parallel, the model can simultaneously attend to different aspects of feature correlations. In each Transformer layer, the multi-head attention is followed by a feed-forward neural network, consisting of two linear transformation layers and a ReLU activation function, further enhancing feature expressiveness. Meanwhile, Layer Normalization and residual connections are employed to stabilize the training process and alleviate gradient vanishing problems.

In the final stage of the model, global average pooling is used for feature aggregation of Transformer output, followed by regression prediction through a three-layer multilayer perceptron. To improve model generalization ability and prediction accuracy, the following strategies are adopted during training: 1) Using dropout (ratio 0.1) to prevent overfitting; 2) Employing Adam optimizer with warmup strategy for learning rate adjustment; 3) Using mean squared error as the loss function with L2 regularization to constrain model parameters. Experimental results show that this hybrid architecture not only effectively captures complex relationships between air quality parameters but also demonstrates better prediction performance compared to using CNN or Transformer alone, with average prediction error reduced by more than 15 percentage. The model design fully considers the characteristics of air quality assessment tasks, achieving high-precision air quality prediction through reasonable structure design and optimization strategies.

Through this hierarchical feature extraction and global modeling method, the model can simultaneously process feature correlations at both local and global scales, providing an effective deep learning solution for air quality assessment. The model output can serve as an important reference for environmental monitoring and decision support.

## IV. Experiments and Analysis

### A. Data Preprocessing and Feature Engineering

*a) Data preprocessing*: This study uses the "Air Quality and Pollution Assessment" dataset from the Kaggle platform, which contains approximately 5,000 air quality monitoring records. The dataset covers 9 key environmental features: Temperature, Humidity, PM2.5, PM10, NO2, SO2, CO, Proximity to Industrial Areas, and Population Density, along with corresponding Air Quality assessment results. For data quality issues in the original dataset, this paper adopts systematic preprocessing methods. First, analyzing data completeness revealed approximately 3.2 percentage missing values in PM2.5 and PM10 features. Considering the temporal characteristics of air quality data, these missing values were filled using moving averages within time windows, a method that better maintains temporal continuity. For anomaly detection, the box plot method was employed, marking data points beyond Q3+1.5IQR or below Q1-1.5IQR as anomalies. These anomalies were handled using winsorization rather than simple deletion to maintain data integrity. Additionally, due to significant differences in measurement scales and value ranges among features (e.g., PM2.5 ranges from 0 to 500 μ g/m³ while CO concentration typically ranges from 0 to 10ppm), Min-Max normalization was applied to scale all features to the [0,1] interval, eliminating scale effects. Finally, the preprocessed dataset was randomly divided into training, validation, and test sets in an 8:1:1 ratio to ensure objective model evaluation. These preprocessing steps significantly improved data quality, laying a reliable foundation for subsequent feature engineering and model training [17].

*b) Feature engineering*: As shown in Fig. 2's feature correlation heatmap, this paper conducted correlation analysis and feature engineering on the preprocessed features to deeply understand intrinsic feature relationships and enhance model performance. Analysis reveals strong positive correlation (0.77) between SO2 and CO, suggesting potential commonalities in emission sources for these gaseous pollutants; NO2 shows significant correlation (0.73) with temperature, reflecting temperature's notable influence on NO2 formation and decomposition; PM2.5 demonstrates strong correlation (0.71) with industrial area proximity, indicating industrial activities as a major source of particulate pollution. Based on these findings, new feature combinations were constructed: Temperature-Humidity Index (THI) was created using temperature and humidity data, showing strong correlation (0.68) with humidity, validating its effectiveness in describing atmospheric conditions; addressing pollutant synergistic effects, ratio features were introduced among

major pollutants (PM2.5, PM10, NO2, SO2); considering air quality's temporal periodicity, time encoding features were added. Additionally, logarithmic transformations were applied to industrial area proximity and population density to reduce data distribution skewness. Through these feature engineering strategies, the model's air quality prediction capability was enhanced while maintaining feature interpretability.

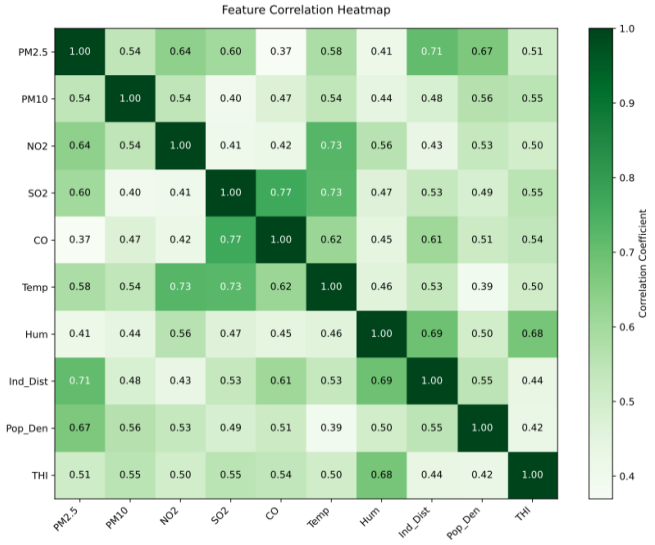


Fig. 2. Correlation heatmap of environmental features.

## B. Evaluation Metrics

Root Mean Square Error (RMSE) was selected as the primary evaluation metric for assessing air quality prediction model performance. RMSE effectively measures the deviation between predicted and true values, with its calculation results maintaining consistency with the dependent variable's scale, facilitating intuitive understanding of model prediction accuracy. Moreover, since RMSE imposes greater penalties on larger errors (through squaring error terms), it is particularly suitable for air quality prediction tasks requiring high accuracy in anomaly value prediction. The RMSE calculation Formula (3) is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

where, n is the sample size, $y_i$ is the true value of the i-th sample, and $\hat{y}_i$ is the corresponding predicted value.

Additionally, this paper adopts the coefficient of determination ($R^2$) as a supplementary evaluation metric for model performance. $R^2$ reflects the degree to which the model explains dependent variable variability, with values ranging from [0,1], where values closer to 1 indicate better model fitting. Compared to RMSE, $R^2$'s advantage lies in its standardized scoring interval, facilitating horizontal comparison of model performance across different datasets [18]. The $R^2$ calculation Formula (4) is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

where, $\bar{y}$ is the mean of all true values, the numerator represents the residual sum of squares, and the denominator represents the total sum of squares.

## C. Comparative Experiments

As shown in Fig. 3, to comprehensively evaluate the performance of the proposed CNN-Transformer hybrid model, this paper selected a series of representative machine learning and deep learning models for comparative experiments. Linear Regression (LR) serves as the baseline model to verify linear relationships in the data; Support Vector Regression (SVR) was selected for its advantages in handling nonlinear problems and high-dimensional data; Random Forest (RF) and Gradient Boosting (GB) represent ensemble learning methods, capable of effectively handling complex feature interactions; XGBoost, as one of the most popular ensemble learning frameworks, possesses strong feature learning capabilities; Deep Neural Network (DNN) represents the baseline performance of traditional deep learning methods on this task. The selection of these models covers multiple technical categories from simple to complex, from traditional to modern, providing a comprehensive comparison basis for evaluating our proposed hybrid model.

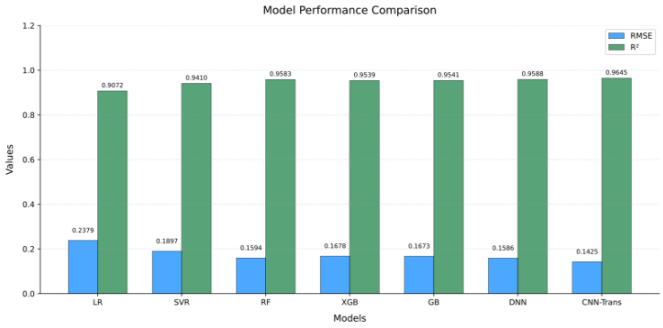


Fig. 3. Performance comparison of different models for air quality assessment.

Analysis of experimental results shows that among traditional machine learning methods, linear regression performed worst (RMSE=0.2379, $R^2$=0.9072), indicating that air quality assessment problems exhibit obvious nonlinear characteristics; Support Vector Regression improved model performance through kernel function mapping (RMSE=0.1897, $R^2$=0.9410); ensemble learning methods (RF, XGBoost, and GB) performed similarly and all outperformed the previous two, with Random Forest achieving the best results (RMSE=0.1594, $R^2$=0.9583); Deep Neural Network slightly outperformed Random Forest (RMSE=0.1586, $R^2$=0.9588), while our proposed CNN-Transformer hybrid model achieved optimal performance (RMSE=0.1425, $R^2$=0.9645). These results demonstrate that our proposed hybrid architecture successfully improved prediction accuracy through CNN's effective local feature extraction and Transformer's capture of global dependencies, reducing RMSE

by 10.2 percentage and improving $R^2$ by 0.57 percentage points compared to the best baseline model, verifying the effectiveness of this method.

### D. Ablation Studies

As shown in Fig. 4, to systematically evaluate the impact of key model components on prediction performance, this paper designed a series of ablation experiments. Specifically, we focused on the following core designs: whether the CNN and Transformer hybrid architecture outperforms single structures; the necessity of positional encoding for maintaining feature sequence information; and the impact of network depth on model performance. These experimental configurations were chosen based on the following considerations: CNN structures excel at local feature extraction while Transformer excels at capturing long-range dependencies, making it essential to verify their synergistic effects for understanding the advantages of the hybrid architecture; positional encoding, as a key component of Transformer, needs verification of its role in air quality assessment tasks involving multi-source feature fusion; meanwhile, considering model complexity and practical deployment requirements, it's necessary to clarify the actual impact of network depth on performance.

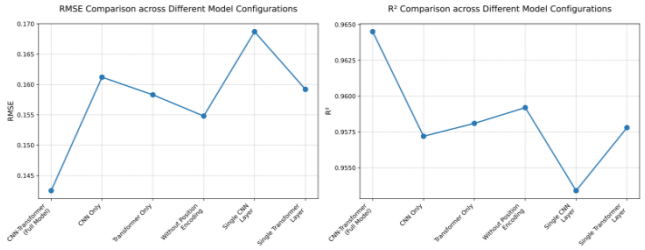


Fig. 4. Results of ablation studies on model components.

Experimental results show that the complete CNN-Transformer hybrid model achieved optimal prediction performance (RMSE=0.1425, $R^2$=0.9650), significantly outperforming other simplified configurations. When removing Transformer and retaining only CNN, model performance decreased significantly (RMSE=0.1612, $R^2$=0.9572), indicating the importance of global dependency modeling in improving prediction accuracy; similarly, the performance degradation when using only Transformer structure (RMSE=0.1583, $R^2$=0.9582) also confirms CNN's irreplaceable value in feature extraction. The importance of positional encoding was verified through comparative experiments, with model performance decreasing after removing positional encoding (RMSE=0.1548, $R^2$=0.9592), indicating that maintaining feature sequence relationships indeed helps improve model performance in air quality assessment tasks. The most significant performance decline appeared in configurations with simplified CNN layers (RMSE=0.1687, $R^2$=0.9534), emphasizing the necessity of deep CNN in progressively extracting complex features; similarly, the performance decline with single-layer Transformer (RMSE=0.1592, $R^2$=0.9578) also indicates the indispensable role of deep attention mechanisms in modeling complex feature correlations. These experimental results not only verify the necessity of each model component but also provide reliable experimental evidence for the hybrid architecture design, confirming the rationality and effectiveness of our proposed method in air quality assessment tasks [19].

### E. Hyperparameter Experiments

As shown in Fig. 5, to determine the optimal model configuration and investigate the impact of different hyperparameters on model performance, this section conducted systematic experimental analysis on Batch Size, Learning Rate, and Dropout ratio. Experiments show that these three hyperparameters significantly influence both the model training process and final performance. Through experiments, we can determine the optimal hyperparameter combination to enhance model prediction performance and generalization ability.


Fig. 5. Impact analysis of different hyperparameters on model performance.

*a) Impact analysis of batch size*: Batch size is a key parameter in deep learning model training, directly affecting model optimization efficiency and convergence performance. This experiment explored five different batch size configurations: 16, 32, 64, 128, and 256. Experimental results show that the model achieved optimal performance (RMSE=0.1425, $R^2$=0.9645) with a batch size of 64. Smaller batch sizes (such as 16), while providing more fine-grained parameter updates, led to unstable training processes and made it difficult for the model to converge to optimal solutions; larger batch sizes (such as 256) reduced model sensitivity to local features, resulting in significant performance degradation. The experiments confirmed that a moderate batch size of 64 achieves a better balance between training stability and model optimization efficiency.

*b) Impact analysis of learning rate*: Learning rate is a crucial hyperparameter determining parameter update step sizes during model training. This experiment examined five different orders of magnitude for learning rates: 0.0001, 0.0005, 0.001, 0.005, and 0.01. Data shows that model performance was optimal with a learning rate of 0.001, achieving RMSE of 0.1425 and $R^2$ of 0.9645. Specifically, too small learning rates (0.0001) led to slow model convergence, requiring more training epochs to reach desired performance levels; while too large learning rates (0.01) caused severe training process oscillations, making it difficult to converge to optimal solutions and potentially leading to training divergence. This result aligns with general experience in deep learning rate setting, namely selecting the largest possible

learning rate while ensuring convergence, to accelerate training speed and improve model generalization ability.

*c) Impact analysis of dropout ratio*: Dropout is an important regularization technique that prevents model overfitting by randomly deactivating neural units during training. This experiment explored five different Dropout ratio configurations: 0, 0.1, 0.2, 0.3, and 0.4. Experimental results show optimal model performance with a Dropout ratio of 0.1, where the model maintained good feature extraction capability while effectively preventing overfitting. Higher Dropout ratios (such as 0.3, 0.4) led to excessive loss of useful feature information, affecting model expressiveness; while completely omitting Dropout (ratio of 0) easily led to model overfitting on training data, reducing generalization performance. This indicates that moderate feature random deactivation is indeed necessary for improving model generalization ability, but the deactivation ratio needs careful control to maintain model expressiveness. Based on these comprehensive hyperparameter experimental results, this research ultimately adopted batch size 64, learning rate 0.001, and Dropout ratio 0.1 as the model's standard configuration. This set of hyperparameters remained constant in all subsequent experiments to ensure result comparability and reproducibility.

## V. Conclusion

This paper proposes an air quality assessment model based on a CNN-Transformer hybrid architecture, achieving high-precision air quality prediction by integrating CNN's local feature extraction capability with Transformer's advantage in modeling global dependencies. Experimental results demonstrate that this hybrid architecture shows significant advantages compared to traditional machine learning methods and single deep learning models, achieving a 10.2percentage performance improvement in RMSE and a 0.57 percentage point improvement in $R^2$. Through systematic ablation experiments, we verified the necessity of each model component, particularly the importance of the CNN-Transformer hybrid architecture, positional encoding mechanism, and multi-layer network structure in enhancing prediction performance.

However, current research still has several limitations. First, the modeling of time series features is not sufficiently comprehensive, especially in handling seasonal variations and long-term trends; second, the model's computational complexity is relatively high, presenting challenges for deployment in resource-constrained environments; furthermore, the model's generalization performance for air quality prediction under extreme weather conditions still needs improvement. These issues provide important references for future research directions.

Future work will primarily focus on the following aspects: 1) Introducing temporal attention mechanisms to enhance the model's ability to handle time series features; 2) Exploring model compression and knowledge distillation techniques to reduce computational complexity and improve model deployment efficiency; 3) Constructing multi-scale prediction frameworks to enhance model prediction accuracy at different spatiotemporal scales; 4) Integrating meteorological knowledge and designing specialized loss functions to improve model prediction performance under extreme conditions [20].

These improvements will further enhance the model's value in practical applications, providing more reliable technical support for air quality assessment and early warning.

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# A Novel Multitasking Framework for Feature Selection in Road Accident Severity Analysis

Soumaya AMRI[1], Mohammed AL ACHHAB[2], Mohamed LAZAAR[3]
Faculty of Sciences in Tetuan, Abdelmalek Essaadi University, Tetuan, Morocco[1, 2]
ENSIAS, Mohammed V University in Rabat, Rabat, Morocco[3]

***Abstract*—In machine learning studies, feature selection presents a crucial step especially when handling complex and imbalanced datasets, such as those used in road traffic injury analysis. This study proposes a novel multitasking feature selection methodology that integrates the Grey Wolf Optimizer, knowledge transfer, and the CatBoost ensemble algorithm to enhance the performance and interpretability of road accident severity prediction. The main objective of this study is to identify critical features impacting the prediction of severe injury cases in road accidents. The proposed framework integrates several steps to handle the complexities related to feature selection. The fitness function of the Grey Wolf Optimizer model is designed to prioritize the classification accuracy of the severe injury class. To mitigate early convergence of the model, a knowledge transfer mechanism that generates new wolf instances based on a historical record of wolves used previously is integrated within a multitasking process. To evaluate the prediction performance of the generated feature subsets, the CatBoost algorithm is employed in the evaluation step to assess the effectiveness of the proposed approach. By Integrating these three step methodology which combine metaheuristic feature selection technique with knowledge transfer through a multitasking process, the proposed framework enhances generalization, reduces prediction models complexity and handles imbalanced distributions. It proposed a feature selection model that overcomes key limitations of traditional methods. Applied to real-world road crash data, the methodology significantly improves the identification of factors impacting the severity of injuries. Experimental results demonstrate enhanced model performance, reduced complexity, and deeper insights into the factors contributing to traffic injuries. These findings highlight the potential of advanced machine learning techniques in improving road safety analysis and supporting data-driven decision-making.**

***Keywords*—Feature selection; road accident; injury severity; Grey Wolf Optimizer; multitasking; knowledge transfer**

## I. Introduction

Machine learning (ML) advancements have created interesting opportunities to solve complex problems in recent research studies. The large amount of collected data serves as an important source of information to train ML models. However, many datasets are subject to a common problem where certain classes, often the most critical, are significantly underrepresented. The analysis of such imbalanced datasets remains a persistent challenge.

This study aims to leverage advancements in machine learning techniques to identify factors associated with severe injuries in road traffic accidents. Through a detailed analysis of crash-related data, this work seeks to enhance the understanding of injury mechanisms and support the development of more effective safety policies and real-time intervention strategies.

In road safety studies, datasets often exhibit imbalanced data problems, and a large number of features are collected. Predicting severe injury resulting from road crashes often involves dealing with imbalanced data distributions. The underrepresentation of minority classes in such datasets, combined with the use of a large number of features, can impact the training and generalization capabilities of traditional machine learning models. It also impacts the complexity of ML models and could lead to overfitting. Guyon explains that domains with a large numbers of input features are susceptible to the curse of dimensionality and multivariate methods may lead to overfitting [1]. The reduction of the number of features can lead to more robust models by mitigating overfitting and enhancing generalization [2].

By isolating the most relevant features and reducing the dimensionality of datasets, feature selection improves the interpretability of prediction models and ensures better focus on minority class prediction. However, traditional feature selection methods often face challenges to balance the needs of minority classes in high-dimensional data, complex interactions between features can hinder models from identifying the critical variables that influence the accuracy of classification. For instance, in road crashes case studies, datasets consists of different feature domains including driver characteristics, crash dynamics, vehicle attributes, and environmental conditions. These various features can interact in non-linear ways, which make it difficult for conventional techniques to effectively identify the most relevant features [3].

These challenges are particularly pressing in the context of road traffic crashes, which remain a global issue, claiming 1.35 million lives and causing around 50 million injuries annually [4]. Such incidents are a leading cause of death, especially among individuals aged 15 to 29, and understanding the factors that influence injury severity is essential for developing effective safety interventions. However, the complex and multifaceted nature of road crash data makes it difficult to accurately identify the critical variables, further underscoring the need for advanced methodologies like the one proposed in this study.

This study proposes a novel feature selection methodology that leverages advanced machine learning models. The proposed framework includes the metaheuristic Grey Wolf Optimizer (GWO), knowledge transfer techniques throw a multitasking process, and the CatBoost ensemble algorithm as a predictor

model. To ensure the effectiveness of the model application in the case study of injury severity prediction in road accidents, a specific implementation of the fitness function of the Grey Wolf Optimizer algorithm is elaborated. By combining these techniques with a specific focus on the accuracy of severe injury predictions, the proposed framework aims to improve the identification of key factors influencing severe injury outcomes in road crashes, and overcome the limitations of traditional approaches.

This paper is organized as follows: The second section presents a literature review of feature selection and machine learning methodologies and techniques, with a focus on road accident feature analysis case studies. The third section outlines the proposed methodology for feature selection using a multitasking framework. The fourth section details the experiments conducted using the proposed feature selection framework. The fifth section presents the experimental results and their interpretations. Finally, the last section summarizes the work presented in this paper and highlights areas for future exploration.

## II. Related Work

### A. Feature Selection Techniques in Machine Learning

Feature selection (FS) step presents an important role in improving the performance of classification studies, especially when using complex and imbalanced datasets where, the presence of underrepresented classes can impact the performance of learning model. FS methods can be divided into two categories of approaches: data-centric and algorithm-centric. Data-centric techniques adjust data distribution to mitigate class imbalance effects through synthetic oversampling, instance weighting, or hybrid resampling strategies that integrate data augmentation with feature selection [5]. To minimize overfitting risks of these techniques, recent research has introduced adaptive synthetic sampling based on feature relevance and the assignment of instance-specific weights [6]. On the other hand, algorithm-centric methods introduce additional techniques to traditional feature selection paradigms (filter, wrapper, and embedded techniques) by incorporating cost-sensitive learning [7], alternative ranking criteria, or hybrid metaheuristics [8], to improve feature selection robustness in skewed distributions. Despite significant advancements in feature selection techniques and results, many challenges persist related to the identification of complex feature interactions, the reduction of computational time for model training and prediction in real-time applications, and early convergence which impacts the models ability to generalize learning in the presence of imbalanced class distributions. Emerging research introduce new feature selection techniques based on deep learning to dynamically weigh features [9]. Reinforcement learning-based feature selection models are used to iteratively refine feature subsets based on classification performance in imbalanced settings [10]. Another emerging technique called evolutionary computations aim to explore optimal feature subsets through population-based search strategies, such as Genetic Algorithms, Particle Swarm Optimization [11], and Grey Wolf Optimizer [12].

The points outlined below presents a detailed overview of cited feature selection methods and their relevance in selecting key factors influencing the performance of minority classes' prediction.

*1) Filter-based methods*: These methods use statistical measures to evaluate features independently of the model. Common techniques are:

- Pearson and Spearman correlation which assess the statistical relationship between features and the target variable [1].
- Chi-square test which evaluates the statistical dependence between categorical features, comparing the observed data with the expected values [13].
- Two-Way ANOVA which is a statistical test used to identify the significant impact of features between two data groups (input and target). The test helps determine whether to accept or reject the null hypothesis [13].

*2) Wrapper-based methods*: Wrapper-based methods use machine learning algorithms to evaluate different feature subsets through three main steps: Generation of feature subsets, training and evaluation of the chosen machine learning model for each subset, and the identification of the best subset that represents the relevant features impacting the target variable [14]. Common wrapper-based techniques include forward selection, backward elimination, stepwise selection, recursive feature elimination (RFE) [15] and genetic algorithms [16]. These methods are model-specific, which allows them to optimize feature selection based on the model's performance. However, they tend to be computationally expensive and are susceptible to overfitting [1].

*3) Embedded methods*: Under the third category of embedded methods, feature selection is seamlessly integrated into the machine learning algorithm itself. These methods not only identify relevant features but also actively suppress the influence of less informative ones, offering a highly efficient solution to feature selection. Key techniques include:

- L1 and L2 Regularization (Lasso and Ridge): These methods incorporate regularization terms into the loss function, shrinking the coefficients of less significant features and promoting sparse, interpretable models.
- Decision Trees and Random Forests: These algorithms inherently measure feature importance by analyzing how frequently a feature contributes to optimal node splits. In Random Forests, the Gini index is commonly employed to quantify this importance, ensuring robust feature evaluation [17].
- Ensemble Methods: Advanced techniques such as gradient boosting and CatBoost go further by quantifying feature contributions to the overall model performance. This enables precise ranking of features based on their predictive power [1].

*4) Hybrid methods*: To identify the most relevant and coherent features, many researchers combine in practice multiple feature selection techniques. This combination of feature selection techniques is referred to as hybrid methods.

Bhyuian used Chi-square, Two-way ANOVA, and regression analysis to identify nine key factors impacting road crash severity from a set of fourteen features [13]. In a similar context or road accident severity prediction, Alkheder employed Chi- square automatic interaction detector trees, Bayesian networks, and linear SVM to identify risk factors and improve classification performance, achieving a testing accuracy of 66% for correct predictions [18]. Kashifi used SHAP analysis and the Gated Recurrent Convolution Network model to identify complex relationships in road accident data [19].

The combination of feature selection techniques in hybrid methods is valuable in complex domains such as road crash injury prediction. It can enhance the robustness of feature selection and improve model performance.

Despite advancements of feature methods such as filter, wrapper, and embedded techniques, these approaches present several limitations related to computational inefficiency, sensitivity to noise, and the risk of suboptimal feature subsets due to local minima entrapment [1], [20].

To overcome these limitations, metaheuristic algorithms have emerged as powerful alternatives using efficient global search strategies. Among these algorithms, the Grey Wolf Optimizer, which is inspired by the social hierarchy and cooperative hunting behavior of grey wolves, demonstrated its ability to balance exploration and exploitation [21]. The concept of this algorithm aims to identify optimal feature subsets, it consists of dynamically updating candidate solutions based on a fitness function to assess the relevance of generated candidates. However, due to its random initialization of candidate solutions, the standard GWO model may face stagnation in later iterations and sensitivity to initial parameter settings. This necessitates further enhancements to improve its robustness and adaptability, such as hybridization with machine learning techniques [22], [23].

### *B. Road Accident Features Analysis*

Feature selection is closely linked to the choice of data architecture model during the data collection phase. Data architecture determines the number of collected features, consistency, and detail of features. Well-chosen features can lead to accurate and meaningful insights, while poor feature selection may result in misleading conclusions.

In road crash studies, key features for accident analysis have been refined over the years by road safety experts. The European Road Assessment Program (EuroRAP) established standardized protocols to display the safety level of a road, offering a common framework for communication [24]. Regular updates are recommended to adjust the evolving nature of road and environmental factors, vehicle characteristics, and driver profiles. These features also vary depending on the national context and the specific road safety strategies in place, adapting to the unique challenges and priorities of each region. However, during the data engineering phase, data analysts often create additional features to highlight new aspects that are not adequately represented by the original, collected features. These engineered features provide a deeper understanding of the data, revealing hidden patterns and relationships.

To cover sector-specific aspects of this study, an analysis of data dictionaries of road crash injury studies has been conducted to identify the key characteristics of the data architecture model for road crash injury datasets and elaborate a specific feature engineering map for road crashes datasets (see Fig. 1).

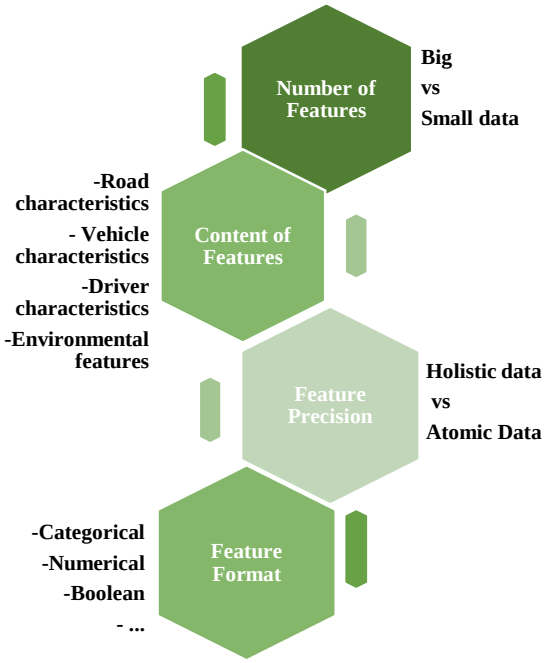


Fig. 1. Feature engineering map for road crashes datasets.

The presented road crash feature map highlights four main characteristics of the architecture of a road accident data inventory:

- Number of features: The number of features varies significantly across studies, ranging from as few as 8 to as many as 50 features. A key measure is introduced to differentiate between Big and Small Datasets, referring to the volume of data, whether large-scale or limited in scope.
- Content of features: The features are typically classified into four broad categories: road features, vehicle features, driver features, and environmental features.
- Feature value format: Features vary in their data format, including categorical, numerical, and Boolean types.
- Precision of feature description: The level of detail in feature descriptions, particularly for categorical values, differs significantly. Some studies provide specific and detailed descriptions (e.g., road surface type, weather conditions), while others are less detailed (e.g., broad classifications of road conditions). Holistic/Atomic Data: Indicating whether the dataset includes broad, comprehensive features (holistic) or more granular, individual characteristics (atomic).

The proposed feature engineering map serves two main purposes:

- Pre-use Tool: It can be applied before the creation of a road accident dataset. In this phase, the map helps to identify the key features that need to be collected or derived, guiding the data acquisition process. This ensures that the dataset is built with relevant and meaningful features from the outset, facilitating a more efficient and effective analysis later on.
- Post-use Tool: Once a road accident dataset has been created and data is collected, the map can be utilized to classify the dataset based on the identified features. It helps in evaluating the quality of the features and the dataset as a whole, allowing for the selection of appropriate machine learning techniques. Based on the results from the feature engineering map, relevant algorithms and models can be chosen to enhance prediction accuracy, handle data imbalances, or optimize for specific outcomes.

## III. Methodology

To perform the prediction capability of machine learning models using feature selection techniques, this paper proposed a multitasking feature selection framework using knowledge transfer and metaheuristic optimization algorithm. The proposed framework implements a feature selection process using the Grey Wolf Optimization, a metaheuristic optimization algorithm inspired by the hunting behavior of wolves. It aims to identify the most relevant features for a classification task. The proposed framework performs multiple tasks (feature selection iterations) where it optimizes feature subsets independently. For each task, the fitness function of GWO based on precision of severe injuries class evaluates the selected features using cross-validation and a CatBoost classifier.

To enhance the computational performance of the model, a knowledge transfer method is incorporated in the model by storing the historical wolves (feature subsets) evaluated in previous tasks and the best historical performance achieved by a feature subset which is represented by a wolf instance. Before each initialization of the wolf instance parameters, the model checks the historical wolves list, and generates new instance of wolf. This technique enhances the computational performance by avoiding redundant computations of used wolves.

One of the major limitation of wolf optimizer algorithm is the risk of stagnation in later iterations. To avoid this problem, the multitasking process is introduced in the proposed model. Combined to the knowledge transfer method described before, each task explores the historical list of wolves, generates new instances of wolves achieving a better performance than the stored best feature subset. This technique countermeasure an eventual fast convergence of the model.

Given the issue of imbalanced data and the strong representation of the non-severe accident class, the fitness function in the proposed model is designed to prioritize the precision of the severe injuries class. This configuration allows the model to focus its performance on improving the prediction of the minority class, which will result in feature subsets that primarily impact the severe injuries class.

Finally, the best feature subset is used to train a final model and evaluate its performance on a test set, focusing on precision for classifying the severe injuries class.

Fig. 2 presents the framework of the proposed multitasking feature selection model.

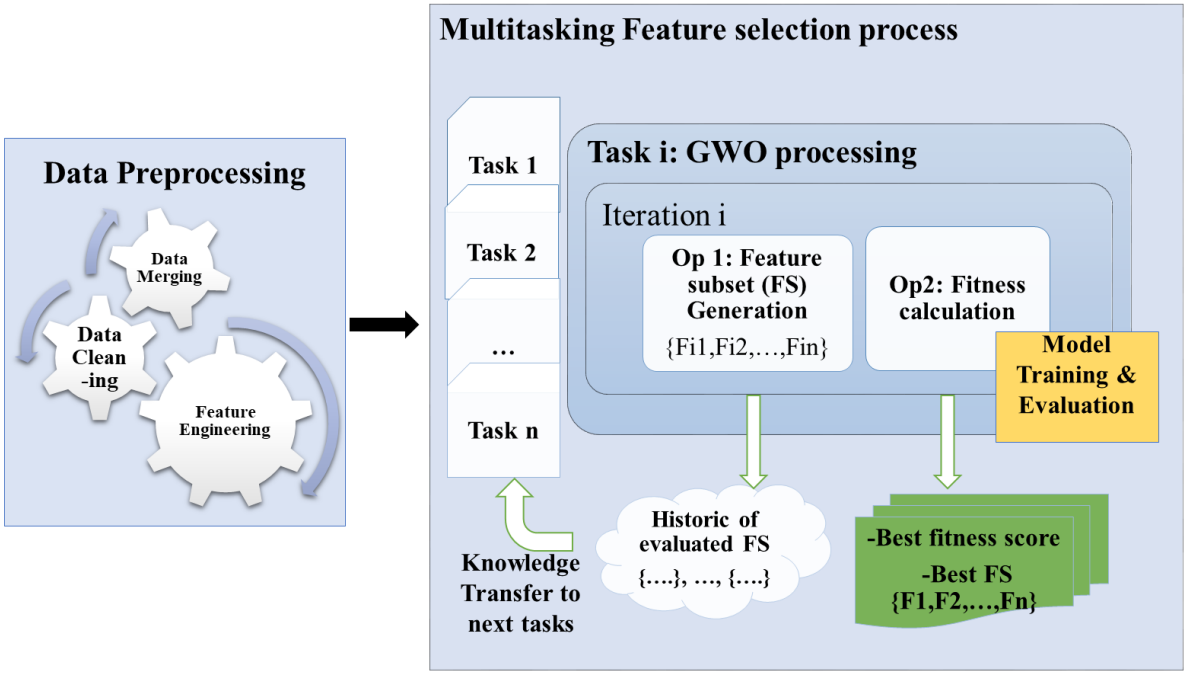


Fig. 2. Framework of the proposed multitasking feature selection model.

### A. Grey Wolf Optimizer Processing

The proposed model employs Grey Wolf Optimization as the core of the multitasking feature selection framework. Inspired by the social hierarchy and hunting strategy of grey wolves, the search process of this metaheuristic algorithm is guided by four types of wolves called alpha, beta, delta, and omega. The alpha wolves represent the best solutions, while beta and delta are used to refine the search, and omega wolves explore new possibilities. The Grey Wolf Optimizer algorithm updates the positions of candidate solutions in a manner similar to the encircling, chasing, and attacking behaviors observed in wolf groups [21]. This allows the model to ensure an optimal selection of relevant features by balancing exploration (searching for new solutions) and exploitation (refining the best solutions).

GWO uses a fitness function to evaluate the score of selected wolves. The default fitness function is designed for general-purpose optimization tasks relying on minimizing an error function or maximizing an objective function without domain-specific adaptations. In this work, the proposed fitness function is tailored specifically to prioritize generated wolves involving the most performant classification accuracy of severe injury class. CatBoost classifier is used as the evaluation component in the classification step. In addition, cross-validation is employed to assess generalization ability and prevent overfitting. This specific adaptation of the fitness function of the Grey Wolf Optimizer algorithm ensures that the most informative features impacting severe injuries are retained, leading to a more accurate classification process and aligning the feature selection process with the specific objectives of this study.

### B. Multitasking Feature Selection

The second layer of the proposed framework consists of a multitasking process. This layer aims to enhance the robustness of the Grey Wolf Optimizer process and address its limitations related to the risk of stagnation in later iterations. In standard GWO, the search process may converge prematurely depending on the initially generated candidates. This may result to suboptimal feature subsets if diversity among candidate solutions is not ensured. The proposed framework integrates a process of multiple optimization tasks that run iteratively. Each task initializes the initial parameters and can then generate a new space of feature subsets. Inspired by multitasking evolutionary computation [25], this mechanism strengthens the exploration process operated by the Grey Wolf Optimizer. It enhances the overall feature selection process by ensuring that different feature subsets spaces are explored to identify a final subset that is both optimal and robust for classification.

### C. Knowledge Transfer Processing

The third layer of the proposed framework aims to improve the efficiency of the multitasking layer by incorporating a knowledge transfer mechanism between the iterative tasks. The GWO algorithm randomly initialize the positions of candidate solutions (wolves), which represents potential solutions in a search space. The major limitation of using only the first layer of feature selection with GWO and multitasking is that tasks could be initialized with similar initial candidate solutions. This process may lead to a repetition of tasks that adds unnecessary computational time without providing additional value. The role of the knowledge transfer layer introduced in this framework is to transfer exploration information from previous tasks to subsequent ones, providing additional factors that refine the initialization of the Grey Wolf Optimizer parameters.

The knowledge-transfer layer records two main data types: the historical list of wolves explored in previous tasks, and a list of the best-performing solutions encountered earlier. When a new task begins, it first examines the data provided by the knowledge-transfer layer and then generates new instances of wolves, with the aim of improving classification performance based on the previously stored best subsets. By incorporating this knowledge, the optimization process benefits from the accumulated experiences of earlier tasks, leveraging them to find better feature subsets more efficiently.

Algorithm 1 describes the proposed framework including GWO processing, fitness function, multitasking feature selection and knowledge transfer mechanism.

**Algorithm 1:** Multitasking FS processing

```
Input:
   X, y: Original dataset.
   num_tasks: Number of optimization tasks.
   num_wolves: Number of wolves (binary feature
   selection vectors).
   max_iter: Maximum number of iterations.
Output:
   SF: Best Feature Subset;
   Model: Trained CatBoostClassifier.
Initialize
Compute
Split X and y into training (X_trainval, y_trainval)
   and test sets (X_test, y_test);
Define fitness_function(selected_features):
   | Extract selected columns from X_trainval
   |       based on the binary vector;
   | Train CatBoostClassifier using cross-validation
   | on the selected features;
   | Compute and return the mean precision score
   | for class of severe injuries;
Initialize
best_global_precision = 0 and previous_wolves = ∅;
For each task t = 1 to num_tasks do
   | Initialize wolves as random binary vectors
   |     (num_wolves × num_features);
   | Set local best fitness = 0;
   | For iteration i = 1 to max_iter do
   |     | For each wolf w = 1 to num_wolves do
   |     |     |   If wolf w exists in
   |     |     |   previous_wolves:
   |     |     |     Regenerate wolf w randomly;
   |     |     |   End
   |     |     |   Compute Fitness(w) =
   |     |     |   fitness_function(wolf w);
   |     |     |   Add wolf w to previous_wolves;
   |     |     |   End
   |     | End
   |     | Identify alpha, beta, delta as the top 3
   |     | wolves based on fitness;
   |     | For each wolf w = 1 to num_wolves do
   |     |     |   Update wolf w's position using
   |     |     |   GWO update formulas with
   |     |     |   alpha, beta, delta;
   |     | End
```

```
    |       | Update local best fitness if a better
    |       | solution is found;
    |   End
    |   If task's best fitness > best_global_precision,
          Update best_global_precision and SF;
    | End
End
Select features from X_trainval and X_test based on
SF;
Train final CatBoostClassifier on the selected
features of X_trainval;
Evaluate the model on X_test and compute the final
precision score for class 1;
Return SF and trained Model.
```

## IV. Experimentation

### A. Data Description

To verify the effectiveness of the proposed multitasking feature selection framework, an open data source of real data obtained from the annual road traffic accident databases managed by the French National Interdepartmental Observatory of Road Safety (ONISR) is used for the experiments. Each bodily injury accident -defined as an event occurring on a public road, involving at least one vehicle, and resulting in at least one victim requiring medical care- is recorded by law enforcement agencies that respond to the scene. This information is captured in a document called the Bodily Accident Analysis Report. The collection of these reports forms the national database of traffic-related bodily injuries, commonly referred to as the "BAAC file," overseen by ONISR.

The annual datasets extracted from the BAAC file include all bodily traffic accidents in mainland France. The research utilizes data from 2005 to 2020. The recorded accident data contains detailed information, covering aspects like crash characteristics, location, involved vehicles, and road users.

To create the input dataset for this study, tables were merged using foreign keys specified in each data file, resulting in a unified dataset. After combining 64 data files -four files for each year- the final dataset consisted of 2,380,573 entries and 57 features, which formed the basis for the analysis in this research.

### B. Data Visualization

To comprehend the variation of features impacting the severity of injuries in road crashes, a univariate and multivariate statistical exploration of the dataset is conducted. The analysis was developed in accordance with a classification according to four views:

*1) Temporal and atmospheric conditions view*: Features involved in this exploration are year of crash, day of week, month, is holiday, in addition to atmospheric conditions and brightness. The temporal exploration shows a significant variation of killed and injured hospitalized road users when distribution is by month and day of week. An increase of the number of accidents is detected on summer and Fridays, road traffic at these periods should be investigated to ensure the real impact. Atmospheric conditions statistics show a slight amount of crashes with light rains (see Fig. 3).

*2) Road characteristics view*: This part of the analysis explores a bivariate statistical view of features related to road characteristics where crashes are produced. Statistics shows that seven features have a visible variation of number of crashes and severity injury: road localization, road category, type of intersection, mode of circulation, road profile, road plan shape and surface state. Crashes are more frequent at urban zones, outside of intersections and bidirectional roads. Departmental, municipal, national roads and highways are respectively road categories involving the highest number of crashes, especially hospitalized and killed ones (see Fig. 4). Most crashes occurred on flat roads and straight sections with normal surface state.

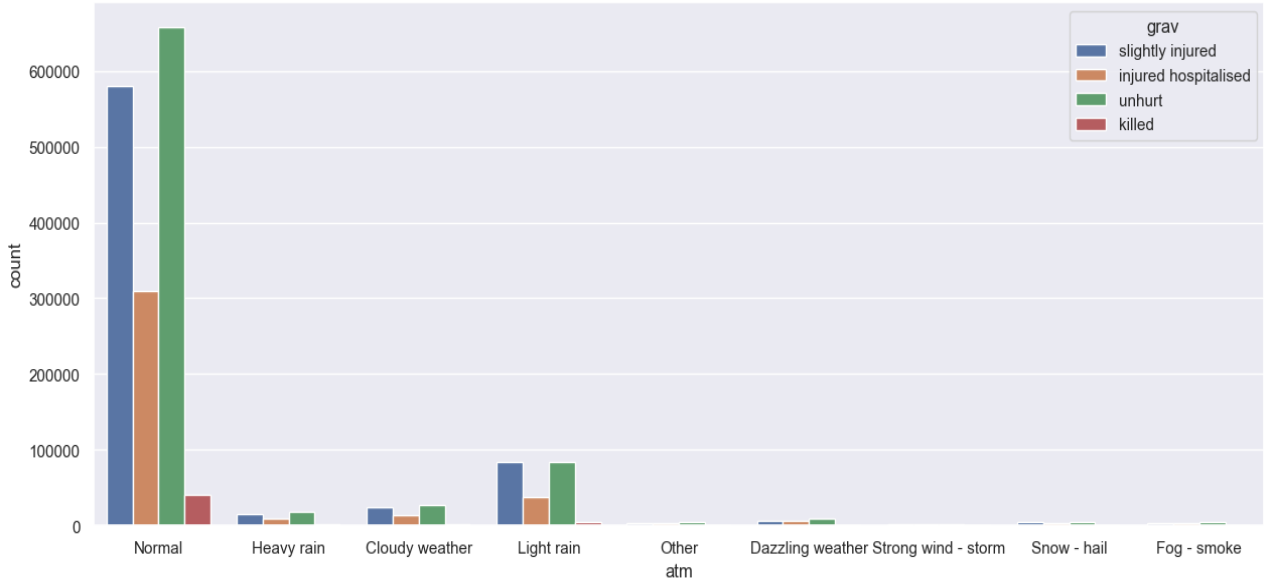


Fig. 3. Distribution by atmospheric conditions.

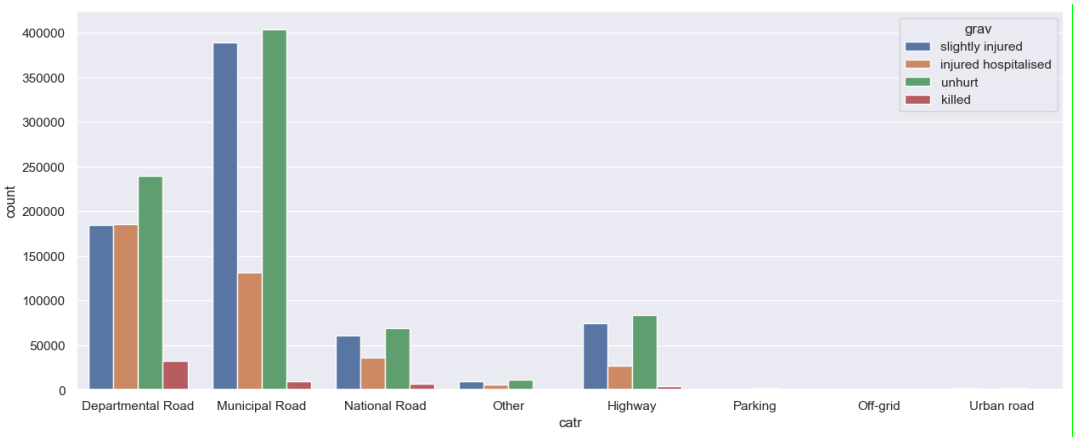


Fig. 4. Distribution by road category.

*3) Vehicle characteristics view*: Regarding vehicle features, features having the highest impact on number of crashes and severe (killed and hospitalized) injuries are category of vehicle, initial shock point, place of the road user into the vehicle, type of collision and main maneuver before the crash. Light vehicles alone have a domination of number of crashes and severe injuries. A significant impact is noted for frontal and side collisions of two vehicles and non-change direction maneuver before the crash. The place of the driver is the riskiest place in vehicles with a surrounding number of 300000 of hospitalized injuries and killed between 2005 and 2020.

This view aims to analyze features related to road user profile. An analysis of the distribution of crashes according to road user profile features (category, gender and age slice) and according to behavioral features (reason of travel at time of accident) is elaborated with a focus on localization on the road of pedestrian victims.

The statistical analysis shows that category of user displays a significant impact on injury severity: pedestrians and passengers face approximately same risk of being killed or hospitalized (see Fig. 5), but drivers are exposed to the highest risk. This statement matches with previous results related to the analysis of crashes' distribution by user place at vehicle.

- User profile view:

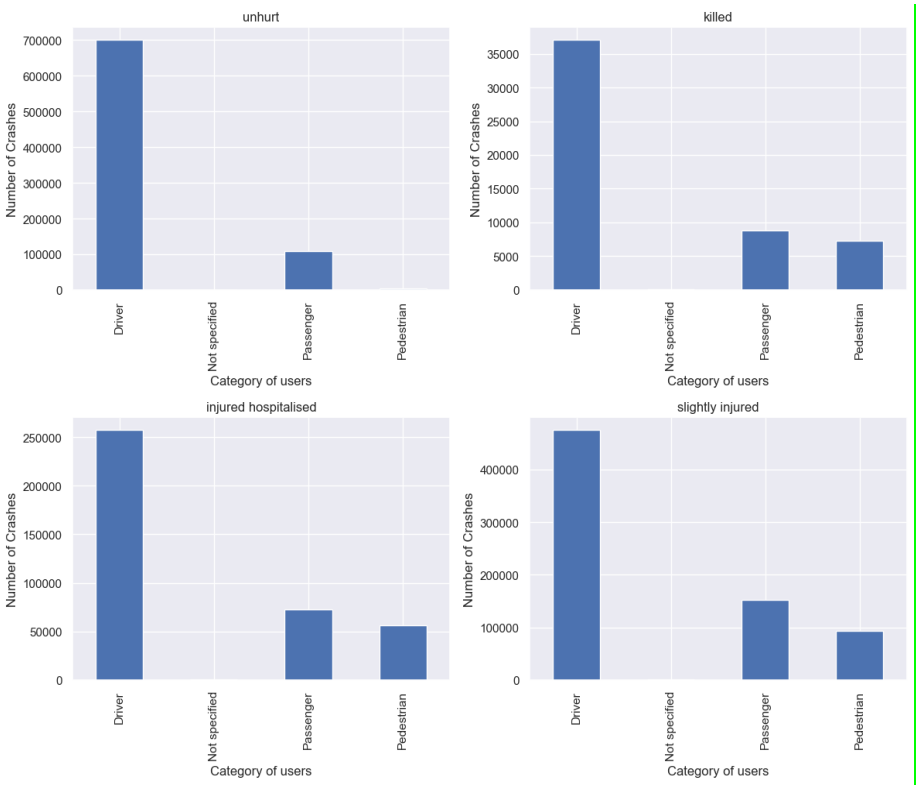


Fig. 5. Distribution by road user category.

Distribution by age slice and gender presents a significant variation. Men and users having 15 to 34 years old and 45 to 65 presents the highest category of killed and hospitalized victims as shown in Fig. 6.

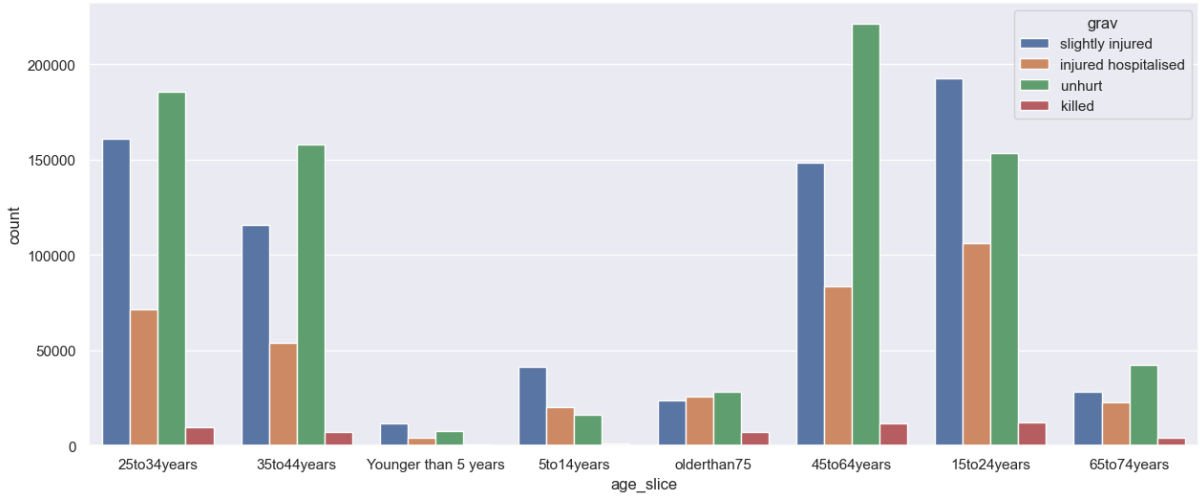


Fig. 6. Distribution by injury level and age slice.

The behavioral analysis presents a static peak of the value “leisure walk” for the fourth injury severity levels. Localization of pedestrians have also a direct impact on injury severity which is higher at areas far than 50m from the pedestrian crossing.

The bivariate statistical analysis highlights several features impacting the injury severity variation. Three groups of features from different views present converged results with a convergent impact. The 1st group of features (place, category of user) presents a significant impact on the risk of injury for drivers. The 2nd group (reason of walk, month, day of week, surface state) presents a neutral impact in leisure trips. The 3rd group (maneuver before the accident, mode of circulation, initial choc point, road plan shape, road profile, type of intersection) presents a higher impact on the risk of severe injuries for frontal crashes. Category of vehicle and road category present a significant singular impact on injury severity.

### *C. Data Preprocessing*

To prepare the studied dataset, the first steps of data cleaning and feature engineering are elaborated. Additional features were derived from the columns "date," "time," and "user date of birth" to explicitly represent embedded information: "time slice", "year", "month", "day", "day of week", "is holiday", "age", and "age slice".

*1) Multitasking feature selection process*: The experimental process in this study aims to optimize feature selection for road traffic accident classification using the proposed multitasking feature selection framework (MFS) based on the Grey Wolf Optimizer. The objective is to identify the most relevant features from the dataset that contribute to accurately predicting severe accidents.

The dataset is initially split into training-validation (75%) and test (25%) subsets using stratified sampling to maintain class balance. The feature selection process is then executed over multiple tasks, where each task consists of several candidate solutions (wolves) exploring the feature space. Each wolf represents a binary vector indicating selected features.

The fitness function used in the MFS framework evaluates the precision of a CatBoost Classifier using 5-fold cross-validation. It measures the model's ability to correctly classify severe accidents (class 1) based on the selected features. The equation for the proposed fitness function is expressed as:

$$F(S) = \frac{1}{k} \sum_{i=1}^{k} Pi(S) \quad (1)$$

where,

- F(S) is the fitness value for a given subset of selected features S.
- k is the number of cross-validation folds (here, k=5).
- Pi(S) is the precision score for class 1 in the i-th cross-validation fold, computed as:

$$Pi(S) = \frac{TPi}{TPi+FPi} \quad (2)$$

where,

- TPi (True Positives) is the number of correctly predicted severe accidents in fold i.
- FPi (False Positives) is the number of non-severe accidents incorrectly classified as severe in fold i.

The objective is to maximize F(S), ensuring that the selected feature subset leads to the highest precision in classifying severe accidents.

The precision score for class 1 (severe accidents) is used as the performance metric. Throughout multiple iterations, the best-performing wolves (α, β, and δ) guide the position updates of the other wolves using adaptive coefficients. This iterative search process refines the feature selection, aiming to maximize classification precision.

Ultimately, this strategy helps the algorithm converge more effectively toward the best feature set, improving the classification model's precision in identifying severe accidents.

After completing all tasks, the best feature subset is selected based on the highest recorded precision. The final CatBoost model is then trained on the training-validation set using the selected features and evaluated on the independent test set. The test performance is measured using the precision score for class 1 to assess the model's ability to correctly identify severe accidents.

## V. Results and Discussion

This section presents the experimental results for the multitasking feature selection framework using the road accident dataset. Three aspects are evaluated in this study: the model's performance; the effect of computational time on training and prediction; and the impact on model complexity, including an analysis of factors influencing the prediction of injury severity in road accidents.

### A. Performance of the MFS Model

*1) Convergence to the best feature subset*: To evaluate the performance of the techniques used in the MFS model for identifying impacting factors and its capability to overcome the limitations of GWO through multitasking and knowledge transfer, an analysis of the generated wolves in each task and iteration during the data processing step is conducted. Table I presents an excerpt from the log file of the generated feature subsets during processing.

TABLE I. Excerpt from the Log File of Generated Feature Subsets

| Iteration | Wolf Number | Feature Subset | Fitness value |
|---|---|---|---|
| **5** | 1 | [0 2 4 5 8 9 10 11 12 13 14 15 16 17 18 22 24 25 28 30 31] | 0,6430 |
| **5** | 2 | [1 2 4 5 8 9 12 13 14 16 17 18 24 25 28 29 30 31] | 0,6356 |
| **5** | 3 | [0 2 4 5 8 11 13 14 15 16 17 18 25 28 29] | 0,6201 |
| **5** | 4 | [0 2 4 5 8 9 11 12 13 14 16 17 18 24 25 28 29 30 31] | 0,6388 |
| **5** | 5 | [2 5 9 10 12 13 14 16 24 25 30 31] | 0,0000 |
| **5** | 6 | [0 2 3 4 5 8 9 12 13 14 16 17 18 21 22 24 25 30] | 0,0000 |
| **5** | 7 | [0 2 4 5 8 9 10 12 13 14 16 17 21 22 24 25 29 30 31] | 0,0000 |

The analysis of the log file presented in Table I reveals that GWO generates many new wolves (feature subsets) that had already been used in previous tasks. The additional layer of knowledge transfer introduced in the MFS framework effectively addresses this limitation. By leveraging the historical set of previously generated wolves, the model minimizes the reuse of feature sets. The fitness function of previously used wolves is automatically set to 0, as shown in Table I, encouraging the generation of new feature sets. This, in turn, enhances the chances of identifying the best feature subsets.

The proposed MFS model represents a significant improvement over classic GWO in generating impactful feature subsets while preventing rapid convergence to suboptimal solutions.

*2) Prediction of severe injuries*: The impact of the MFS framework on the prediction accuracy of injury severity levels is evaluated using classification metrics derived from the injury severity level predictions. Table II presents the prediction metrics obtained using the CatBoost classifier with the feature subset generated by the MFS framework and the metrics obtained using the CatBoost classifier on the entire dataset before applying feature selection.

TABLE II. Results of Injury Severity Level Prediction

| Model | Prediction using MFS framework output | | | Prediction using Catboost without Feature selection | | |
|---|---|---|---|---|---|---|
| | Precision | Recall | F1-score | Precision | Recall | F1-score |
| **Class 0** | **0.87** | 0.96 | 0.91 | 0.85 | 0.94 | 0.89 |
| **Class 1** | 0.65 | 0.35 | 0.45 | **0.68** | 0.41 | 0.51 |
| **Accuracy** | | | **0.84** | | | 0.83 |
| **Macro avg** | 0.76 | 0.65 | 0.68 | 0.76 | 0.68 | 0.70 |
| **Weighted avg** | 0.83 | 0.84 | 0.82 | 0.81 | 0.83 | 0.81 |

The results shows that the overall accuracy of the model is slightly higher when using the MFS framework output. While the precision for class 1 (severe injury) is slightly lower, the precision for the non-severe injury class is improved. The general analysis shows that the MFS framework maintains the prediction performance.

### B. Computational Time of MFS Model

To evaluate the computational time gain of the proposed model, a comparison is made between the fitting and prediction times of the CatBoost model using features generated by the MFS framework and the CatBoost model using the initial features before the implementation of the MFS, as presented in Table III.

TABLE III. COMPUTATIONAL TIME COMPARISON

| Computational time (seconds) | MFS framework | Initial Catboost | Percentage of gain |
|---|---|---|---|
| Fitting | **190.607** | 209.35 | **-9%** |
| Prediction | **0.212** | 0.389 | **-44,7%** |

The computational time comparison shows that the MFS framework enhances efficiency over the initial CatBoost model, particularly in prediction time. The fitting time decreases from 209.35 seconds to 190.607 seconds, achieving a 9% reduction, indicating a slight improvement in training efficiency. More notably, the prediction time drops from 0.389 seconds to 0.212 seconds, resulting in a 44.7% reduction. This demonstrates that the MFS framework significantly improves computational efficiency by reducing both training and prediction times. The most remarkable gain is in prediction time, where the MFS framework nearly halves the required time, making it much more suitable for real-time or large-scale predictions.

### C. Complexity of the Model

The results presented before shows that the proposed MFS framework help to identify a reduced feature subset that maintain the prediction accuracy of the injury severity level.

This feature selection process reduced the model's complexity from 35 features to 10, representing a 75% reduction in complexity.

### D. Analysis of Impacting Factors

The highest precision is achieved using the selected subset of features, which includes: ['day', 'int', 'catr', 'circ', 'plan', 'surf', 'infra', 'situ', 'catv', 'obs', 'manv', 'catu', 'trajet', 'age_slice'].

This series of features generated using the MFS framework identify the factors that significantly influence the prediction of injury severity in road crashes. These features are systematically categorized into four principal groups, each representing a distinct dimension of the accident context and contributing to the overall predictive model.

*1) Temporal and atmospheric conditions*: By selecting only two key features -day of occurrence and surface conditions- to represent atmospheric conditions instead of incorporating a broader range of related variables, the overall model complexity is significantly reduced. This streamlined approach captures the essential environmental influences while mitigating redundancy and overfitting risks.

*2) Road features*: Features in this group relate to the geometric and infrastructural characteristics of the roadway. To reduce model complexity while retaining critical information, related features resulting from the MFS framework are: intersection typology, road classification, circulation modes, horizontal alignment (road layout), the state of road infrastructure, and the specific situational context of the accident. This curated selection effectively characterizes the essential physical environment in which the crash occurs, thereby playing a critical role in determining accident severity while mitigating redundancy.

*3) Vehicle Features*: The vehicle category is included in the selected feature subset. This inclusion may be attributed to the high incidence of road crashes involving light vehicles, which are classified as category 7, as illustrated in Fig. 7

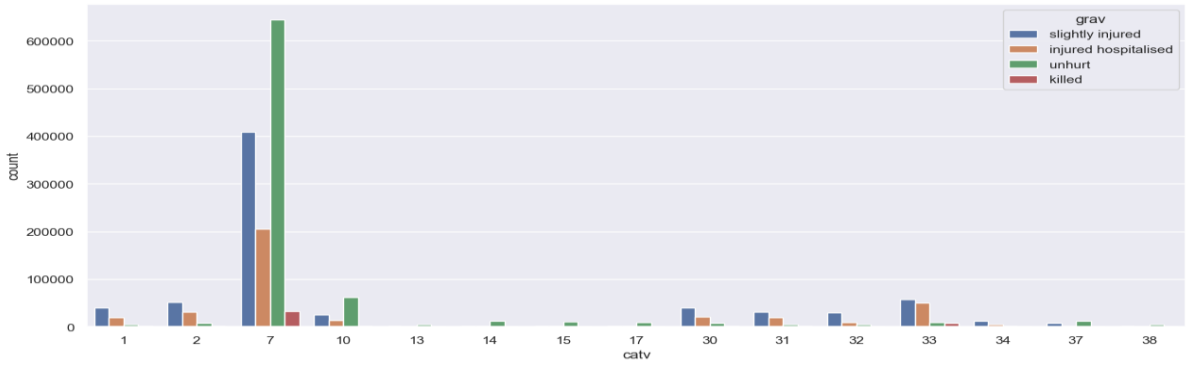


Fig. 7. Distribution of road crashes by category of vehicles and level of injury severity.

*4) User profile*: The user profile group is incorporated into the selected feature subset by including key demographic and behavioral indicator, specifically, age stratification and the primary reason for travel at the time of the accident. This streamlined selection effectively captures essential aspects of the human element in road safety, reflecting behavioral patterns and decision-making processes that are empirically linked to variations in injury severity, all while reducing overall model complexity.

The comprehensive integration of these selectively chosen feature categories underscores the multifactorial and complex interplay among environmental, infrastructural, vehicular, and human factors that collectively determine injury severity in road crashes. The focus on the most representative features from each group resulting from the multitasking feature selection framework, reduces model complexity while preserving critical information. Consequently, it enhances the understanding of factors impacting road safety and facilitates the development of more robust and interpretable predictive models for injury severity assessment.

## VI. CONCLUSION

This paper presents a multitasking feature selection framework for predicting severe injuries caused by road crashes. This novel approach to data analysis and feature selection

combines three layers of learning to identify features impacting severe injuries in road crashes. It combines the strengths of the Grey Wolf Optimizer, the advantages of multitasking, the knowledge-transfer mechanism and the Catboost classifier to effectively reduce the complexity of large datasets and improve the classification performance of predictive models.

The metaheuristic algorithm GWO serves as a robust optimization tool to identify relevant features impacting the classification of injury severity. The multitasking process ensures a wide exploration of potential feature subsets. On the other hand, the knowledge transfer mechanism ensures the efficiency of the multitasking process leading to improved generalization and faster convergence.

Experimental results validate the efficacy of the proposed framework, it demonstrates its superiority over conventional methods in terms of feature selection efficiency, complexity reduction, predictive performance, and significant reduction in computational time. These findings suggest that the framework can be held for improving the performance of machine learning models in road safety data analysis and even across a variety of other domains. In future work, the MFS framework could be integrated into a safety countermeasure system, offering the possibility to adjust factors influencing severe injuries in real time. Due to its adaptability, the framework could be further refined and applied to more complex datasets across various domains, especially in real-world applications dealing with large-scale data. However, the overall performance of the proposed framework depends on the initial performance of the model used to compute the fitness function within the GWO algorithm. This dependency may limit the framework's adaptability and generalizability.

## ACKNOWLEDGMENT

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# Assessment of Remote Sensing Image Quality and its Application Due to Off-Nadir Imaging Acquisition

Agus Herawan[1], Patria Rachman Hakim[2], Ega Asti Anggari[3], Agung Wahyudiono[4], Mohammad Mukhayadi[5], M. Arif Saifudin[6], Chusnul Tri Judianto[7], Elvira Rachim[8], Ahmad Maryanto[9], Satriya Utama[10], Rommy Hartono[11], Atriyon Julzarika[12], Rizatus Shofiyati[13]

Research Center for Satellite Technology, National Research and Innovation Agency, Bogor, Indonesia[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]
Research Center for Limnology and Water Resources, National Research and Innovation Agency, Bogor, Indonesia[12]
Research Center for Geoinformatics, National Research and Innovation Agency, Bogor, Indonesia[13]

***Abstract*—One advantage of using microsatellites for remote sensing is their maneuverability so that the target area can be captured from any viewing angle based on specific needs. However, the image captured under off-nadir acquisition will have reduced quality in both geometry and radiometric aspects. This research aims to find the effect of off-nadir acquisition on remote sensing image quality in general and its accuracy on land use land cover (LULC) application based on LAPAN-A3 microsatellite image data. Both images from the nadir and off-nadir acquisition of one specific target, which had several days/weeks difference, are compared to the nearest Landsat-8 image data. Based on several target images used in this research, the imaging viewing angle indeed affects the quality of the remote sensing images, both in general image quality and land use land cover application accuracy. The degradation of LULC accuracy can be considered acceptable however, where in general, it can be modeled to -0.5 percent/degree, i.e., an image taken under 20 degrees off-nadir acquisition will have reduced 10 percent accuracy. This result shows that the off-nadir microsatellite imaging technique can be used for specific remote sensing needs without compromising quality.**

***Keywords*—Land cover; land use; LAPAN-A3; microsatellite; off-nadir; revisit time**

## I. Introduction

Microsatellites are quite popular these days for remote sensing missions due to their low cost and flexibility to accommodate specific missions. Research Center for Satellite Technology (PRTS-BRIN) has already launched three micro-satellites, one of which was the LAPAN-A3 satellite. Its main missions are remote sensing and maritime monitoring for the Indonesian region. The satellite has an RGB-NIR multispectral imager with a 15-meter resolution and an RGB digital matrix camera with a 3-meter resolution. The multispectral one has consistently produced daily images for Indonesia region coverage since its launch in 2016. Still, the payload has made significantly fewer images in the past two years due to its age. Aside from providing daily images for the Indonesia region like any other international satellite such as Landsat and Sentinel, the LAPAN-A3 satellite is also often used for specific missions based on requests from users from various institutions in Indonesia, both for research and operational purposes.

One of the most common requests from users is to capture one specific target with high frequency in a relatively short period, for example, for imager vicarious calibration [1], monitoring the effect of natural disasters [2], or other remote sensing application [3]. These requests are not feasible in regular satellite operation in nadir acquisition since the satellite and its imaging payload usually have a fixed revisit time, which depends on satellite orbit and imager swath width. For example, the Landsat-8 payload has a revisit time of 16 days, and two Sentinel-2 satellites have a combined 5 days revisit time [4], [5], [6], while the multispectral imager of LAPAN-A3 has 21 days revisit time. An off-nadir acquisition technique must be employed to capture one specific target on earth more often than the revisit time. During acquisition, the roll angle of the satellite, which rotates the satellite left and right, is adjusted so that the imager can capture the area far away from the satellite ground track [7], [8].

However, images taken under off-nadir acquisition usually have lower quality than those taken under nadir acquisition, both in terms of geometric and radiometric points of view. Geometrically, the image produced will have a lower modulation transfer function (MTF) [9], and also will not have a square pixel when projected to the earth's surface, where the shape and size distortion of the projected pixel depends on a combination of three-axis angles, i.e., yaw, pitch, and roll angle [10]. In the radiometric aspect, the images will have different sunlight illumination compared to nadir acquisition [11], which, in some cases, could produce a sun-glint effect [12], [13]. Although the off-nadir images could serve well for naked-eye inspection and manual interpretation, these two disadvantages could raise some questions about the quality of the resulting images when used for remote sensing applications, such as land use and land cover (LULC) [14], [15], among others. However, this is not a trade-off between image quality and imaging frequency for one particular target area since nadir acquisition will produce precisely one perfect image in one revisit time interval. In contrast, the off-nadir acquisition will produce one ideal image and several distorted images, so the off-nadir technique will always be better in this case. Instead, is it worth sacrificing another area that could not be captured that day in favor of distorted off-nadir images? If the quality of off-nadir images is good, it is well worth it because the user request will be considered successful. Still, if the quality is not good, doing an off-nadir acquisition could be considered a waste of time.

This research aims to find the effect of off-nadir acquisition on the quality of the image produced, both in terms of general image quality and in terms of accuracy of remote sensing application, in this case land use land cover, with Landsat-8 images being used as reference. The classification accuracy of two images that captured one specific target, one taken under nadir and one under off-nadir acquisition with about several days/weeks difference of acquisition time, is compared. The research uses several target areas, classification algorithms, and classes for each case to properly conduct the analysis. Besides classification accuracy, general image metric quality, including blurring and brightness effects, will be analyzed to show further off-nadir acquisition's impact on the resulting image captured. This research will also explore other aspects of LAPAN-A3 satellite operation regarding off-nadir acquisition technique, such as satellite attitude comparison and solutions to irregular path-rows that the satellite had since it did not have a propulsion system to adjust the orbit during its seven years of operation. The outcome of this research would be to show that the off-nadir acquisition technique could be one of the methods to solve remote sensing needs or missions requested by the user.

Section II will discuss off-nadir acquisition of LAPAN-A3 satellite, theory about generic image quality analysis, as well as method of land use and land cover (LULC) classification for LAPAN-A3 satellite imagery using maximum likelihood and minimum distance algorithm. Results, analysis, and some discussions are presented in Section III, while conclusion and some recommendations are presented in Section IV.

## II. Methodology

In general, this research can be divided into three parts. In the first part, the off-nadir acquisition technique employed on the LAPAN-A3 satellite will be described, including the basic theory of satellite maneuver, the resulting satellite attitude during observation, and an example of using the technique to solve specific tasks. In the second part, the quality of images produced under off-nadir acquisition will be compared to images under nadir acquisition, both in general image analysis and the accuracy of LULC classification. Finally, the advantages and disadvantages of using the off-nadir technique will be discussed, and some suggestions will be given.

### *A. Off-Nadir Acquisition of LAPAN-A3 Satellite*

LAPAN-A3 satellite uses the momentum bias technique as a control strategy to keep the satellite at nadir during observation by using a star tracker sensor (STS) and gyro as attitude sensors as well as a reaction wheel and magnetorquer as attitude actuators [16]. In momentum bias control, only one wheel and three magnetorquers are used to maintain the satellite in the nadir position, thus saving power consumption. Although the momentum bias could be executed automatically, in actual LAPAN-A3 satellite operation, manual interference by the satellite operator is needed, mainly to take corrective action to ensure that the satellite perfectly points in the nadir position. The average attitude angle of the satellite during observation since its launch in 2016 is about under 2 degrees for all yaw, pitch, and roll angles, which is quite good. As a small satellite, LAPAN-A3 also suffers from attitude nutation, which has a pattern of the sinusoidal-like curve in roll angle with 0,3 amplitude and a period of 70 seconds. Fig. 1 shows a mosaic of the Indonesia region from LAPAN-A3.

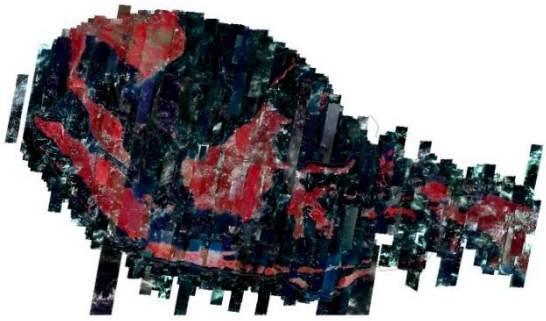

Fig. 1. Mosaic of Indonesia region of LAPAN-A3 multispectral images in nadir pointing.

As stated earlier, one advantage of using momentum bias control is reducing power consumption. However, it has disadvantages when it comes to satellite maneuvers. While it is straightforward in other control techniques to do off-nadir maneuvers, it is not so straightforward in the momentum bias technique. LAPAN-A3 satellite uses two off-nadir maneuver techniques, i.e., inertial pointing and pure-roll nadir pointing [17]. The attitude maneuver needed in the most common maneuvers is only roll angle, i.e., the angle that rotates the satellite left and right when moving forward. Out of the two, the inertial pointing technique is arguably the more straightforward to implement since it only needs to set both pitch and roll angle to some predetermined value once before and once after the acquisition. However, in inertial pointing, the pitch angle of the satellite i.e., the angle that rotates the satellite forward and backward when moving forward, is set to zero degrees (nadir position) only in the latitude of the target area. This produces non-uniform pixel spacing, where pixel which is far from the target (in along-track direction) will have longer pixel compare to pixel in target area. In the other hand, pure-roll nadir pointing technique needs more complex pre-determined set of command to set angular velocity of both roll and pitch angle. This pure-roll nadir technique produces more uniform image pixel spacing since the pitch angle will always be adjusted to zero degrees (nadir position) at any given time. Fig. 2 compares the concept of inertial pointing and pure-roll nadir pointing.

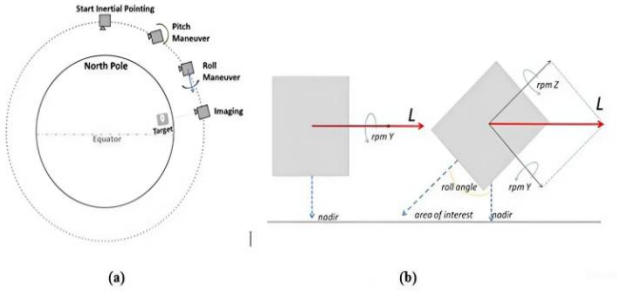


Fig. 2. Off-nadir technique: (a) inertial pointing vs. (b) pure-roll nadir pointing

### *B. Generic Image Quality Assessment*

Depending on the value of the roll angle needed, images produced in off-nadir acquisition often have significant

distortion in both geometric and radiometric aspects. Blurring and irregular pixel shape are two examples of geometric distortion that might occur [18], [19], [20], [21]. Pixel shape and size can be theoretically calculated by using standard co-linear projection, while blurring effect can be evaluated from the attitude profile produced by the star tracker sensor. Several other image quality metrics are commonly used to analyze the degradation of distorted images [22], [23]. However, most of these metrics can hardly be seen visually from an image by the naked eye or visual interpretation unless the image is zoomed in to the highest detail.

Another image metric that will be evaluated is the radiometric aspect of the images that degenerated due to off-nadir acquisition. One prominent example is the sunlight reflection angle. In nadir observation, the incident angle of sunlight coming from the sun, reflected by the object, and entering the camera usually has a nominal value, which is the same from day to day, depending on the satellite's equatorial crossing time. In off-nadir acquisition, since the roll angle can be set randomly, there might be a chance that the sunlight will reflect perfectly from the surface into the camera, which will cause the images to be too bright or often saturated [20]. To measure this problem, the histogram approach is used for each band of the imager, where the difference in each histogram curve can measure the level of distortion.

Several metrics above are standard metrics used to analyze image quality to compare its quality to the quality of the original image, which is often considered a perfect or ideal reference. While these general image analyses are usually enough to describe the quality of distorted images, this research will further analyze the effect of off-nadir acquisition on the quality of the images captured by using a remote sensing application approach, which is land use land cover (LULC) classification [24], [25].

### *C. Land Use and Land Cover Classification*

The off-nadir images used in this research are LAPAN-A3 multispectral images taken for the on-field vicarious imager calibration process. Several on-field vicarious calibration campaigns were conducted from 2017 to 2022 in several target areas in Indonesia, which needed highly uniform bright areas such as deserts or karst mining areas. Jaddih (East Java) and Kupang (NTT) were two areas that were used for the LAPAN-A3 multispectral imager calibration process. The ideal satellite image that should be used for calibration is the image taken from the nadir acquisition. However, in case of cloudy observation or general failed acquisition, each campaign always takes two or three acquisitions in consecutive days. In three-day type of acquisition, the second day will give nadir images, while the first and last days give an extreme off-nadir image with around a 40 degree roll angle in the opposite direction. On the other hand, in the two-days type of acquisition, no nadir image was captured both images were taken from slight off-nadir acquisition, around 15 to 20 degrees of roll angle, in the opposite direction. Table I shows the data used in this research, consisting of the date and location of the image, as well as the imaging viewing angle for each data.

TABLE I. LAPAN-A3 MULTISPECTRAL DATA

| Target Area | Acquisition Date | Roll angle | Image Status |
|---|---|---|---|
| Case 1 Data: Kupang | 11 April 2018 | -11 degree | Clear |
| Case 1 Data: Kupang | 12 April 2018 | +29 degree | Clear |
| Case 1 Reference: Landsat-8 | 29 April 2018 | Nadir | Clear |
| Case 3 Data: Jaddih | 29 Oct 2018 | -40 degree | Cloudy |
| Case 3 Data: Jaddih | 30 Oct 2018 | +1.5 degree | Clear |
| Case 3 Data: Jaddih | 31 Oct 2018 | +40 degree | Clear |
| Case 3 Reference: Landsat-8 | 30 Oct 2018 | Nadir | Clear |

LAPAN-A3 multispectral images used in this research have been systematically corrected for lens vignetting radiometric distortion, band co-registration geometric error and geo-referenced using Landsat data as reference. The classification process consists of three main stages, i.e., pre-processing data, class classification, and accuracy test using reference data, as seen in Fig. 3. A critical step in the pre-processing stage is geo-referencing off-nadir images, where the image is often heavily distorted geometrically due to the significant viewing angle. Thus, the process needs to be conducted carefully. The classification uses supervised and unsupervised approaches [26], [27], [28]. In supervised classification, two standard algorithms are used, i.e., minimum distance and maximum likelihood [29], [30], to show the consistency of the result. Several classes of land cover are used in the classification process, such as water bodies, vegetation, human-made structures, and open areas, among others, depending on the image evaluated. Moreover, the two images of the nadir and off-nadir images generally have short, different times of time acquisition to ensure the fairness of classification comparison.

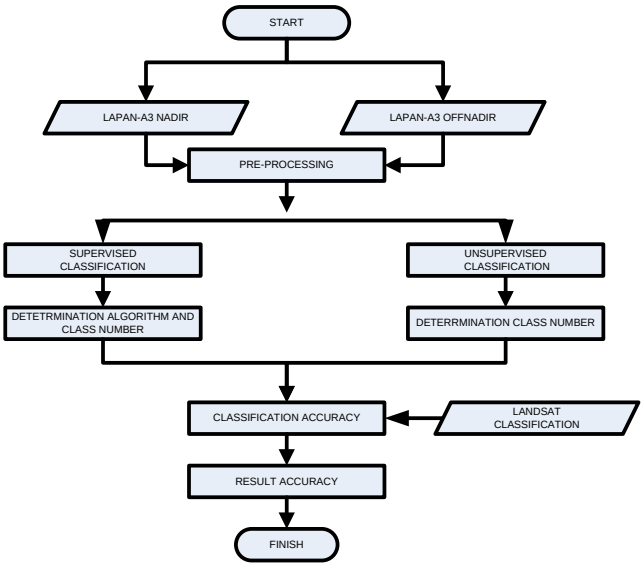


Fig. 3. Image classification (LULC) procedure.

Classification results of LAPAN-A3 multispectral images, both nadir image and off-nadir image, are then compared to the nearest Landsat image to produce classification accuracy of each image. The focus of this research is to analyze the characteristics of the classification accuracy curve concerning roll viewing angle, i.e., how far the accuracy falls when the

viewing angle is increased. The actual accuracy itself is not the focus of this research because the actual accuracy is heavily influenced by imager quality or, in other terms, the cost of the satellite. Several studies have been done previously related to the exact classification accuracy of LAPAN-A3 multispectral images [31].

## III. Result and Discussion

### A. Improvement of Imager Revisit Time

As mentioned earlier, one of the advantages of using micro-satellites for remote sensing is their ability to maneuver so that the satellite can capture the area that is not on its ground track, thus increasing the frequency of acquisition of one particular location at the expense of not capturing another area. In nominal operation, the LAPAN-A3 multispectral imager has 21 day revisit time. However, with off-nadir technique acquisition, the frequency could be increased, with roll angle allowance determining how often the area could be captured. Based on the simulation, mathematically, Table II shows revisit time improvement of the LAPAN-A3 multispectral imager concerning the roll angle allowed, with several percent overlaps between images. It can be seen that, in the most common assumption of 50 percent image overlap, the revisit time could be improved from 21.49 days to 5.14 days if a 20-degree roll angle is allowed. If a 40-degree roll angle is permitted, the revisit time could be further improved to 2.36 days, which was the case of both LAPAN-A3 multispectral imager acquisition of the Palu natural disaster and the calibration campaign.

TABLE II. Revisit Time of LAPAN-A3 Multispectral Imager

| Roll angle allowed | Overlap 90% | Overlap 50% | Overlap 10% |
|---|---|---|---|
| Nadir | 121.75 | 21.49 | 12.18 |
| Roll 10 deg | 12.59 | 8.49 | 6.52 |
| Roll 20 deg | 6.30 | 5.14 | 4.30 |
| Roll 30 deg | 3.97 | 3.48 | 3.07 |
| Roll 40 deg | 2.57 | 2.36 | 2.17 |

In actual implementation, the imager was able to produce seven images under two weeks duration, averagely about 2 days of revisit time, when monitoring the effect of earthquake in Palu (Sulawesi) in 2018. Out of these seven images, one image was taken from nadir position, four images taken from slight off-nadir position, and two images taken from extreme off-nadir position. Although most of the images were heavily distorted, the images were successfully used to complement other satellite data to evaluate the effect of the earthquake. Fig. 4 also shows the results of the off-nadir acquisition of the Jaddih karst area on 29 to 31 October 2018 for the imager calibration campaign, where, the imager could produce three images in three consecutive days [32]. Nadir's image was taken on the second day of the campaign, while the other two images were taken from the extreme off-nadir position, because the roll angle was around 40 degrees, it can be seen that off-nadir images are heavily distorted, thus subject to quality degradation, which will be analyzed in the next section.

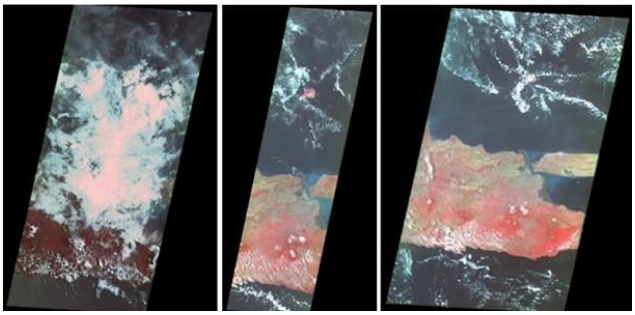

Fig. 4. Vicarious calibration images of the Jaddih area on October 2018, 3 images in 3 days.

### B. Off-Nadir Image Quality Analysis

Before analyzing the image quality of the resulting off-nadir images, satellite stability in all three axes will be compared between nadir and off-nadir acquisition. The stability of the imager during observation is essential since it directly affects the geometry aspect of the images. Fig. 5 shows the profile comparison of yaw, pitch, and roll angle during observation in nadir and off-nadir acquisition. The values of all angles have been normalized to make analysis easier, where each angle value in one particular axis has been subtracted from its average angle value during observation. In general, the pure-roll technique could replicate nadir pointing behavior quite well, while the inertial pointing technique could not. The most notable disadvantage of inertial pointing is pitch angle drifting, about 6 degrees in 90 seconds, which could produce non-uniform pixel spacing, especially in long observation. However, inertial pointing techniques outperform pure-roll technique and nadir pointing in terms of roll and yaw angle behavior, where it could reduce the nutation effect significantly. The pure-roll technique still inherits a sinusoidal-like profile caused by the nutation effect, just like in nadir pointing. In the image domain, both pitch drifting and nutation effects will make image geo-location much harder, especially for long images. Therefore, localized image geo-location should be conducted to produce an accurate result.

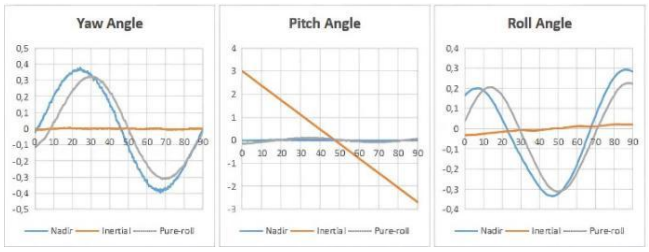


Fig. 5. Satellite attitude comparison between nadir and off-nadir observation (Y: degree, X: second).

The blurring effect is evaluated to further analyze the quality of the off-nadir image, particularly in terms of geometry. While previous analyses focus on a greater picture of attitude profiles, such as drifting and nutation, blurring analyses focus on a more detailed attitude profile. Blurring on an image could be caused by significant movement, be it translational or

rotational, in a short period. Fig. 6, shows this blurring metric, where the rotational movement is recorded by STS every 270 milliseconds. With an image ground sampling distance of 15 meters and a satellite altitude of 500 km, a 1-pixel degree of blurring corresponds to 0.0017 degrees in pitch and roll angle axes. Note that the effect of the yaw angle is not as significant as the other axes. It can be seen that, like previous results, inertial pointing out perform pure-roll technique in yaw and roll axis, while pure-roll technique produces better pitch axis performance. However, by combining blurring effect in pitch and roll angle, pure-roll technique gives a lower blurring effect, thus giving better images. For the actual blurring value itself, at worst, pure-roll produces around 5 pixels of blurring compared to 10 pixels with inertial pointing, assuming the same blurring profile with STS data recorded every line interval of 1.9 ms.

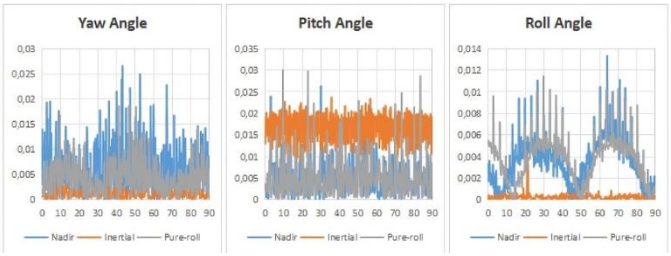


Fig. 6. Blurring effect estimation based on 270 ms attitude data of all axes angle (Y: degree, X: second).

For radiometric aspect, Table III shows comparison of average digital number of image taken under nadir condition and image taken under off-nadir condition. In general out of four bands, off-nadir images produce brighter images compared to nadir images. While brighter image can be considered as good images, it could lead to saturated images, where some really bright object such as cloud, become all-white (saturated). Perfect match between satellite roll angle and sun illumination angle could produce sun-glint effect where sun light is directly reflected by earth surface into the imager. Fig. 7 shows histogram of each band digital number of nadir and off-nadir images for Jaddih area.

TABLE III. AVERAGE OF DIGITAL NUMBER FOR NADIR AND OFF-NADIR IMAGES

| Target Area | Roll Angle | NIR | Red | Green | Blue |
|---|---|---|---|---|---|
| Kupang Slight Off-nadir | -11 degree | 1704 | 4179 | 6215 | 1541 |
| Kupang Off-nadir | +29 degree | 3184 | 8321 | 10787 | 4774 |
| Jaddih Nadir | +1.5 degree | 7175 | 12545 | 14648 | 3938 |
| Jaddih Off-nadir | +40 degree | 9298 | 16668 | 22705 | 12267 |

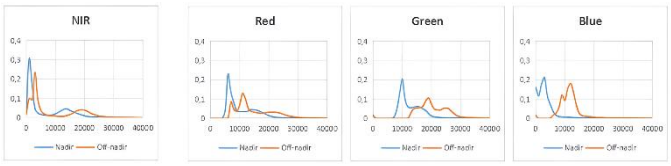


Fig. 7. Histogram of digital number for each band of Jaddih images.

## C. Accuracy of LULC Classification

Ultimately, the quality of off-nadir images produced will be analyzed in the remote sensing domain, using accuracy of land use and land cover (LULC) application. Both supervised and unsupervised classification are used, where in supervised classification, maximum likelihood (ML) and minimum distance (MD) algorithms are used. Table IV and Table V shows a summary of accuracy assessment of the classification, with all parameters considered, i.e., the classification type, the algorithm used, and number of classes. It can be seen that from Jaddih data set, for supervised classification of two classes (water/land) with ML algorithm, the accuracy of nadir images, with a roll angle of 1.5 degree, is about 95.01percent while its off-nadir image with 40 degree roll angle has 88.02 percent accuracy. There are 6.99 percent accuracy degradation which is caused by 38.5 degree increased roll angle. MD algorithm also produces similar result, for the same two classes supervised classification, produces 7.47 percent accuracy degradation. Adding more classes (from two to four) will lower accuracy for both nadir and off-nadir images, but the accuracy difference between the two is more or less similar as previous, 8.06percent for ML and 4.18 percent for MD. Unsupervised classification produces slightly higher accuracy difference between nadir and off-nadir images, with 4.68 percent (two classes), 12.21 percent (three classes), 10.94 percent (four classes), and 13.56 percent (five classes) accuracy difference. Kupang data set result also gives similar patterns, but with lower accuracy degradation, due to lower difference between nadir and off-nadir viewing angles.

TABLE IV. ACCURACY ASSESSMENT OF LAPAN-A3 MULTISPECTRAL OFF-NADIR IMAGES (JADDIH – EAST JAVA)

| Method | Number of classes | Nadir Image (1.5 deg) | Off-nadir Image (40 deg) |
|---|---|---|---|
| Unsupervised | 2 | 83.31% | 78.63% |
| | 3 | 62.30% | 50.09% |
| | 4 | 55.75% | 88.02% |
| Supervised (ML) | 2 | 88.98% | 81.51% |
| | 4 | 51.56% | 43.50% |
| Supervised (MD) | 2 | 55.75% | 44.81% |
| | 4 | 45.69% | 41.51% |

TABLE V. ACCURACY ASSESSMENT OF LAPAN-A3 MULTISPECTRAL OFF-NADIR IMAGES (KUPANG – EAST NUSA TENGGARA)

| Method | Number of classes | Nadir Image (11 deg) | Off-nadir Image (29 deg) |
|---|---|---|---|
| Unsupervised | 2 | 96.36% | 95.84% |
| | 3 | 70.36% | 69.33% |
| | 4 | 67.99% | 62.76% |
| Supervised (ML) | 2 | 97.82% | 95.61% |
| | 4 | 68.12% | 56.22% |
| Supervised (MD) | 2 | 96.30% | 95.76% |
| | 4 | 63.02% | 51.25% |

Fig. 8 shows classification results of the nadir image (a), off-nadir image (c), and its Landsat reference image (b) of Jaddih area by using supervised classification of four classes with Maximum Likelihood algorithm, while Fig. 9 shows the

result of unsupervised classification with four classes. It can be seen visually that nadir images (a) produce more similar result to Landsat images (b) in both cases compared to off-nadir images (c). However, classification results from supervised and unsupervised algorithms are not quite similar in some areas of the image, but this is out of the scope of this research and thus will be investigated in future research.

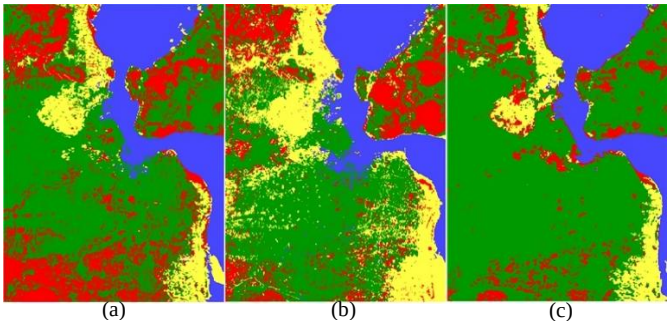


Fig. 8. Four classes supervised classification results of Jaddih using ML algorithm.

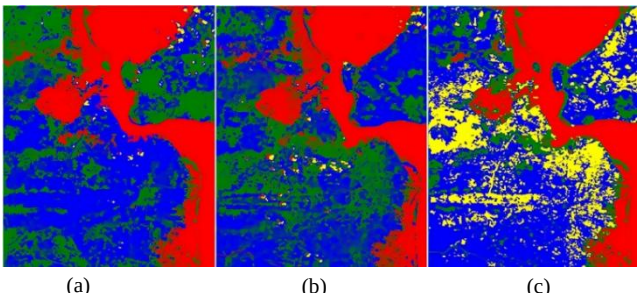


Fig. 9. Four classes unsupervised classification results of Jaddih.

### D. Discussion

The main focus of this research is to find the effect of off-nadir acquisition on the image quality of the produced image, especially for remote sensing applications, which in this case is land use land cover classification. With several adjustable classification configuration, such as classification type (supervised/unsupervised), classification algorithm (maximum likelihood/minimum distance), and number of classes (2/3/4/5), different results were obtained. However, all of these results show that images that were taken under off-nadir observation will produce lower classification accuracy. In this section, a model of accuracy degradation with respect to roll viewing angle will be developed. Different parameter configuration could produce different result. However as previously discussed, the accuracy degradation will not different that much. Based on data from Table IV and V, Fig. 10 shows the distribution of accuracy degradation from all data samples (15 cases), which has an average of -0.25 percent/degree. Discarding some outliers, outside the standard deviation range, at worst, the accuracy degradation can be approximated by -0.5 percent/degree. It means that, in general, the accuracy will decrease 5 percent for 10 degree roll angle increment. For example, there will be a 10 percent accuracy drop when the roll angle is set to 20 degree when the satellite is capturing the target area.

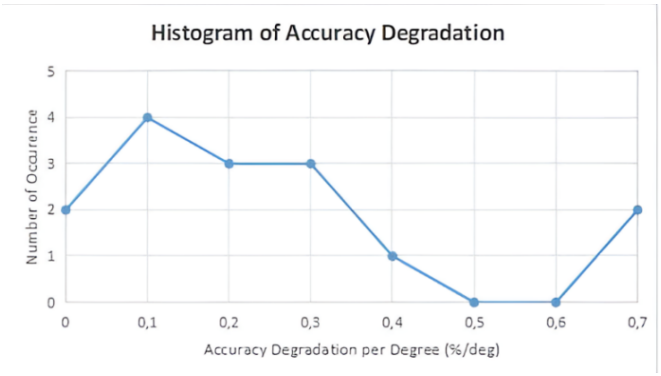


Fig. 10. Distribution of accuracy degradation of all data samples.

Another interesting finding, although not significant and not related to nadir and off-nadir images, is the difference in classification results by using different configurations. First, supervised classification produces better accuracy than unsupervised classification with the same number of classes. Second, classification with fewer number of classes produces better accuracy, which has a straightforward explanation, i.e., more complex classification often produce lower accuracy. Imagine in two-class classification of water body and land surface, the accuracy must be very high, regardless of what type of classification and algorithm is used. Last, the maximum likelihood algorithm produces better accuracy compared to the minimum distance algorithm.

Based on all of these results, i.e., satellite attitude profile, blurring effect, and histogram for generic image quality as well as accuracy of land use and land cover for remote sensing applications, images produced from off-nadir observation suffered acceptable quality degradation compared to images from nadir observation. However, the acceptance level could differ from one application to another and from one user to another. When some users need a perfect image for their application, then off-nadir acquisition is not the solution. However, as previously stated, this is not a trade-off between image quality and frequency of acquisition. Off-nadir acquisition will always be better than nadir acquisition in this aspect, because one optimal-quality image plus several sub-optimal quality images are better than just one optimal-quality image. The disadvantage of using off-nadir acquisition is not the quality of the resulting image, but rather the lost opportunity to capture the area beneath the satellite (nadir on satellite ground track) that could not be done due to the satellite rolling to the right or left of the area. For most cases, when the importance of some specific tasks that need off-nadir acquisition is high, this disadvantage is often acceptable, since the area can be captured in the next revisit time of the satellite payload.

## IV. Conclusion

The off-nadir technique has been employed on LAPAN-A3 multispectral image acquisition in order to increase imaging frequency of one particular target based on specific user needs, where the revisit time could be improved from 21 days to 5 days for 20 degree allowed roll angle and to 2.5 days for 40 degree allowed roll angle. Off-nadir acquisition on the LAPAN-A3 satellite has been successfully executed to monitor the effects

of several natural disasters in Indonesia, as well as to capture calibration sites for several consecutive days. The images produced however, have degraded quality both in generic image quality and in remote sensing application accuracy. Blurring effect could be minimized by using a better off-nadir technique, but the images tend to be bright (saturate) when the satellite is facing into sun reflection direction. For land use/land cover classification application, off-nadir images have about -0.5 percent/deg of accuracy degradation with respect to roll viewing angle, meaning with 20 deg viewing angle, the accuracy is reduced by 10 percent. Some aspects of classification, such as the type, algorithm, and number of classes, are also influence to classification accuracy, but not significantly. These moderate results show that off-nadir multispectral images of the LAPAN-A3 satellite could still be used for land use and land cover classification when high frequency acquisition of one particular area is needed and moderate accuracy is accepted.

Three further research studies could be conducted related to this research. First, a smoother off-nadir technique could be developed to ensure the stability of the satellite when maneuvering so that the image produced will have a better geometry structure. Second, an algorithm for correcting off-nadir images should be developed so that the image quality and remote sensing application accuracy could be improved. Last but not least, the off-nadir technique could be used to increase the uniformity of image coverage for the satellite with no thruster, like the LAPAN-A3 microsatellite. Since without a thruster, the satellite sometimes will enter a period of time where the ground track of the satellite is such that it could not visit one particular area for three months. On the other hand, there are other particular areas that are visited by the satellite several times a month.

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# High-Precision Urban Air Quality Prediction Using a LSTM-Transformer Hybrid Architecture

Yiming Liu[1], Mcxin Tee[2], Liangyan Lu[3], Fei Zhou[4], Binggui Lu[5]
Faculty of Business and Communications, INTI International University, Malaysia[1, 2]
Accounting and Finance Department, Yunnan College of Business Management, Kunming 655000, China[3]
President's Office, Shinawatra University, Pathum Thani 12160, Thailand[4]
Faculty of Education, Shinawatra University, Pathum Thani 12160, Thailand[5]

***Abstract*—With the acceleration of urbanization, accurate air quality prediction is crucial for environmental governance and public health risk management. Existing prediction methods still face challenges in handling complex time-series dependencies and multi-scale features. In this paper, a hybrid deep learning architecture (LT-Hybrid) based on LSTM and Transformer is proposed for high-precision air quality prediction. The model captures the long-term dependencies of time-series data through a two-layer LSTM structure, models the complex interactions among different environmental factors using a multi-head self-attention mechanism, and improves the training stability through a combination of residual connections and layer normalization. Experiments on an urban air quality dataset, containing nine dimensions of environmental characteristics such as temperature, humidity, PM2.5, etc., show that the LT-Hybrid model achieves an RMSE of 0.1021 and an $R^2$ of 0.9382, reducing prediction errors by 13.0% and 5.1% compared to benchmark models of traditional LSTM and XGBoost, respectively. Accurate prediction of air quality indicators provides timely risk assessment for respiratory diseases and cardiovascular conditions, enabling proactive public health interventions. Through systematic ablation experiments and hyperparameter analysis, the validity of each core component of the model is verified, providing a high-precision prediction scheme for environmental monitoring and health risk assessment.**

***Keywords*—Air quality; deep learning; LSTM; transformer; multi-head attention mechanism; temporal prediction; health risk**

## I. INTRODUCTION

Air quality has become a key issue in modern urban development and public health management. With the acceleration of industrialization and urbanization, the spatial and temporal distribution of air pollutants is becoming more and more complex, and the interaction mechanisms between pollutants are more difficult to capture. Accurate air quality prediction not only provides scientific decision support for environmental regulators, but also helps the public to take protective measures in time, which is of great practical significance for improving public health and quality of life [1].

Traditional air quality prediction methods mainly include statistical modeling and numerical simulation. Statistical models such as autoregressive integral sliding average (ARIMA) are computationally efficient and easy to implement, but it is difficult to characterize the nonlinear relationship and long-term dependence between pollutants [2]; numerical simulation models such as community multiscale air quality model (CMAQ) take into account the detailed atmospheric physicochemical processes, but it is computationally expensive and requires a large number of accurate input parameters [3]. In recent years, with the booming development of deep learning techniques, neural network-based prediction methods have shown significant advantages. Among them, Long Short-Term Memory (LSTM) networks are widely used in time-series prediction tasks due to their unique gating mechanism that can effectively capture long-term dependencies, while Transformer models show excellent modeling capabilities when dealing with multivariate sequential data by virtue of their powerful self-attention mechanism [4].

However, existing deep learning methods still face three main challenges in the air quality prediction task: first, although a single LSTM model can model the temporal dependence, it is difficult to effectively capture the complex interactions between different environmental factors; second, the computational complexity of the standard Transformer increases significantly with the length of the sequences when dealing with long sequential data, which restricts its use in high-frequency environmental monitoring data analysis; finally, the common non-stationarity and multi-scale characteristics of environmental data also bring a severe test to the generalization ability of the prediction model [5].

To address the above problems, this paper proposes a hybrid architecture (LT-Hybrid) based on LSTM and Transformer for air quality prediction. The main contributions of this study include 1) proposing a novel hybrid deep learning architecture, which significantly improves the prediction performance by fusing the sequence modeling capability of LSTM and the feature interaction capability of the multi-head self-attention mechanism, reducing the prediction error by 13.0% and 5.1% compared to the benchmark models such as the traditional LSTM and XGBoost, respectively, and 2) designing a two-layer LSTM with a four-headed cascade structure of the attention mechanism, which realizes the adaptive extraction of multi-scale features and enables the model to reach 0.9382 in the $R^2$ evaluation index, which improves 1.66 percentage points compared to a single model; 3) by introducing the combined design of residual linkage and layer normalization, which effectively solves the training problem of the deep network, the ablation experiments show that this design reduces the RMSE of the model from 0.1142 to 0.1021, which improves the prediction stability. The

experimental results show that the proposed LT-Hybrid model can effectively deal with the complex temporal dependencies in air quality prediction, and provides a high-precision prediction scheme for the field of environmental monitoring.

## II. Related Work

### A. Traditional Air Quality Prediction Methods

Air quality prediction studies first used statistical methods. Autoregressive integrated sliding average model (ARIMA) became the main tool for early air quality prediction due to its good performance in time series analysis. Qi et al [6] applied an improved ARIMA model to predict PM2.5 concentration in Beijing, and enhanced the model performance by introducing seasonal adjustment. Another important class of methods is prediction models based on numerical simulation, such as the community multi-scale air quality model (CMAQ). Zhang et al [7] applied the coupled WRF-CMAQ model to regional-scale air quality prediction, which is able to take into account the detailed atmospheric physicochemical processes but is computationally expensive and has stringent requirements on the quality of input data. In addition, machine learning methods such as Support Vector Regression (SVR) and Random Forest (RF) have been widely applied to air quality prediction. Zhai et al [8] constructed a multi-objective prediction framework based on XGBoost, which demonstrated the advantages of dealing with nonlinear relationships.

### B. Deep Learning Based Prediction Methods

In recent years, deep learning has made significant progress in the field of air quality prediction. Recurrent neural network (RNN) and its variant LSTM have become a research hotspot due to its ability to effectively process sequential data. Wen et al [9] proposed a prediction model based on bidirectional LSTM, which improves the prediction accuracy by simultaneously considering the information of historical and future time steps. With the development of deep learning technology, Tao et al [10] proposed a deep learning model based on a one-dimensional convolutional network and a bidirectional GRU, which improves the prediction accuracy by effectively extracting spatio-temporal features. In addition, one-dimensional convolutional neural network (1D-CNN) has been demonstrated to have unique advantages in processing environmental time-series data. Huang et al [11] applied deep residual network to air quality prediction, which effectively mitigated the gradient vanishing problem through jump connections.

### C. Hybrid Modeling and Multi-Source Data Fusion

In order to fully utilize the advantages of different models, researchers have begun to explore hybrid modeling approaches. Yi et al [12] proposed a deep distributed fusion network that significantly improves the prediction performance by fusing heterogeneous urban data to capture all influential factors. In terms of feature extraction, Freeman et al [13] proposed a novel deep learning architecture that improves prediction accuracy through multi-level feature extraction and fusion. Another important research direction is to introduce the attention mechanism for feature selection. Liang et al [14] proposed a deep learning model based on spatio-temporal attention, which is able to adaptively learn the importance of different spatio-temporal features, providing a new idea for air quality prediction. In addition, Yu et al [15] explored an air quality prediction method based on graph neural networks, which achieves high-precision prediction on a regional scale by modeling the spatial correlation relationship between monitoring stations.

These related works have laid an important foundation for the LT-Hybrid model proposed in this paper. Although existing studies have made progress in different aspects, there are still challenges in dealing with complex temporal dependencies and multi-scale feature fusion, which are the directions of focus and improvement in this paper.

## III. Methodology

### A. Problem Statement

Accurate prediction for urban air quality is one of the key tasks in environmental monitoring and management. In this paper, air quality prediction is modeled as a time-series prediction problem: given environmental monitoring data from the past 24 time steps, including nine characteristic dimensions such as temperature, humidity, PM2.5, PM10, NO2, SO2, CO concentration, and the distance to the industrial area and population density, we predict the target air quality indicators for the next time step. This prediction task is obviously challenging: first, the environmental data exhibit complex time-dependence and potential interactions among different pollutants; second, the air quality is affected by a combination of factors, including both dynamic changes in meteorological conditions and cyclical patterns of human activities; and lastly, the environmental data often exhibit nonlinear and non-smooth characteristics, which puts higher demands on the prediction model's generalization ability puts forward higher requirements. Therefore, it is of great practical significance to design a prediction model that can effectively capture these complex patterns.

Formally, if the input feature at the $t^{-th}$ time step is denoted as $x_t \in \mathbb{R}^9$, the prediction task can be formulated as follows: based on the observation sequence $\{x_{t-23}, x_{t-22}, \dots, x_t\}$ predicts the target value $y_{t+1}$. where, the input features contain multi-dimensional information reflecting the current environmental conditions, and the prediction targets focus on specific air quality indicators. With this sliding window approach, the model can continuously predict future air quality and provide data support for environmental regulation and public health decision-making.

### B. Model Architecture

The air quality prediction model proposed in this paper is a hybrid architecture based on LSTM and Transformer, which improves the prediction performance by combining the advantages of both models [16]. As shown in Fig. 1, the model mainly consists of an LSTM coding layer, a multi-head self-attention mechanism, a feed-forward neural network and a normalization layer. Each core component is described in detail below.

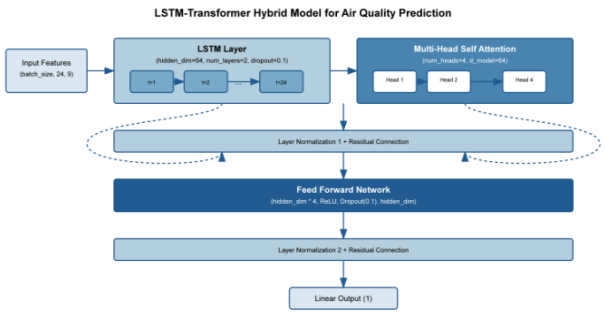


Fig. 1. Model architecture diagram.

### C. LSTM Coding Layer

The LSTM coding layer is the first major component of the model for capturing long-term dependencies in temporal data [17]. Compared with traditional recurrent neural networks, LSTM can effectively mitigate the gradient vanishing problem and better maintain long-term memory through the gating mechanism. The layer adopts a two-layer LSTM structure (num_layers=2) with a hidden layer dimension of 128, and uses dropout=0.1 between layers to prevent overfitting. The core update process for each LSTM cell can be represented as:

$$c_t = f_t \odot c_{t-1} + i_t \odot tanh(W_c \cdot [h_{t-1}, x_t] + bc) \quad (1)$$

In particular, the memory unit $c_t$ realizes selective retention of historical information and selective reception of new information through the modulation of the forgetting gate $f_t$ and the input gate $i_t$.

The LSTM layer receives a 9-dimensional sequence of input features (including environmental indicators such as temperature, humidity, PM2.5, etc.), and the length of the sequence is set to 24 time steps, which enables the model to make predictions based on data from the past 24 time units. This design fully takes into account the temporal characteristics of air quality data, as pollutant concentrations tend to exhibit obvious daily variation cycles and continuity. By cascading the two-layer LSTM, the model can capture the basic temporal patterns in the first layer and further extract the high-level temporal features in the second layer, so as to efficiently learn and memorize the important patterns in the environmental data at different time scales. Especially when dealing with environmental data with complex time dependencies, this cascaded feature extraction structure shows significant advantages.

### D. Multi-Pronged Self-Attention Mechanisms

In order to enhance the model's ability to model the relationship between different time steps in temporal data, a multi-head self-attention mechanism was introduced after the LSTM layer [18]. Traditional attention mechanisms may assign too much attention weight to a single feature or time step, thus ignoring other potentially important information. The multi-head attention mechanism allows for simultaneous attention to different types of feature patterns by projecting the input into multiple subspaces [19]. The mechanism uses 4 attention heads (num_heads=4), each with a dimension of 16 (d_k=d_model/num_heads=64/4=16), and its core computational process can be represented as:

$$\text{Attention}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \text{softmax}(\mathrm{QK}^{\mathrm{T}}/\sqrt{\mathrm{d_k}})\mathrm{V} \quad (2)$$

$$where, Q = HW^Q, K = HW^K, V = HW^V\mathrm{E}$$

The design of multiple heads of attention allows the model to learn feature associations in parallel in different representation subspaces. Each attention head can focus on capturing specific types of dependencies; for example, one head may focus on short-term correlations between temperature and humidity, while another may focus on long-term patterns of association between PM2.5 and other pollutants. Through this parallel processing mechanism, the model is able to model dependencies on multiple time scales simultaneously, capturing both localized patterns of rapid change as well as identifying global trends of long-term change, thus significantly improving the model's ability to understand and predict complex spatial and temporal patterns.

### E. Residual Connections and Layer Normalization

A combination of two residual connections and layer normalization is used in the model, located after the multi-head attention layer and the feedforward network layer, respectively [15]. This design draws on the architectural features of Transformer and helps mitigate the problem of gradient vanishing in deep neural network training. Layer normalization helps to stabilize the training process, while residual connectivity maintains the information of the low-level features, allowing the model to better integrate different levels of feature representation. The use of this architecture significantly improves the training stability and convergence speed of the model.

### F. Feedforward Neural Networks

After the multi-head attention layer, the model uses a feed-forward neural network for feature transformation. The network uses an expansion-contraction structure, where the feature dimensions are first expanded to four times their original size (hidden_dim*4), then nonlinearities are introduced via the ReLU activation function, and finally the dimensions are compressed back to their original size (hidden_dim). The network also uses dropout (rate of 0.1) to prevent overfitting. This component enables further abstraction and transformation of the features extracted by the attention mechanism, enhancing the expressive power of the model.

### G. Output Layer

The final layer of the model is a linear output layer that maps the processed features to a single predicted value. This layer compresses the high-dimensional features extracted and transformed above into a one-dimensional output that directly predicts the target air quality indicator. With this end-to-end architectural design, the model is able to automatically learn the complex mapping relationships from the original input features to the final predicted values.

This hybrid architecture design takes full advantage of LSTM's strengths in sequence modeling and Transformer's

strengths in feature interaction modeling, enabling the model to better handle complex time-series prediction tasks such as air quality prediction.

## IV. EXPERIMENTS

### A. Data Preprocessing

In this study, we use the publicly available dataset "Urban Air Quality Dataset" from the Kaggle platform, which contains the environmental monitoring data of a city during the period of 2020-2023, totaling 5000 records. The dataset covers nine dimensions of environmental characteristics: temperature (℃), relative humidity (%), PM2.5 (μg/m³), PM10 (μg/m³), NO2 (μg/m³), SO2 (μg/m³), and CO (mg/m³), as well as two spatial characteristics: distance from the industrial area (km) and population density of the area (people/km²). The data sampling frequency was hourly, ensuring continuous monitoring of air quality changes.

As shown in Fig. 2, from the time-series distribution of the key features, the temperature values generally fluctuate between 20 and 40°C, reflecting obvious daily changes; the relative humidity has a large range of variation, fluctuating between 40 and 100%, and fluctuates more frequently; and the PM2.5 concentration shows a large fluctuation, with the baseline value between 0 and 40 μg/m³, but with obvious peaks (the highest reaching about 140 μg/m³), reflecting the fact that air quality can deteriorate significantly at certain points in time. The time-series change characteristics of these three key indicators indicate that the air quality of the city is affected by a combination of several environmental factors, showing a complex dynamic change pattern, which provides an important basis for the subsequent predictive modeling.

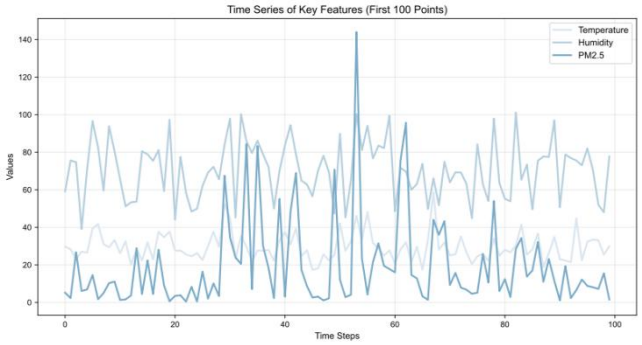


Fig. 2. Time series plot of key features.

### B. Feature Engineering

In order to improve the training effect of the model, this paper carries out a series of pre-processing on the raw data. First, the data are processed for missing values, and the moving average method is used to fill in a small amount of missing monitoring data to ensure the continuity of the data. Second, the individual features are normalized using MinMaxScaler, which maps the data to the [0, 1] interval and eliminates the scale differences brought about by different units of measure. Finally, the sliding window method is used to construct the time series samples, and 24 hours are selected as the length of the input sequence, i.e., the data of the previous 24 hours are used to predict the air quality indicators of the next hour, so as to generate the input-output sample pairs required for model training.

### C. Experimental Setup

For the experimental setup, we adopted a rigorous training-validation-testing framework. First, the processed dataset was randomly divided into a training set (4000 entries), a validation set (500 entries), and a testing set (500 entries) according to the ratio of 8:1:1, and ensured that the continuity of the time series was maintained during the division process. The model was trained using the Adam optimizer with the initial learning rate set to 0.001, and the learning rate was adjusted using the cosine annealing strategy. To prevent overfitting, a regularization strategy with dropout=0.1 was used during training, and an early stopping strategy was applied to the validation set, where, training was stopped when the validation loss did not improve within 10 consecutive epochs.

In terms of model hyperparameter configuration, the LSTM coding layer uses a two-layer structure (num_layers=2), and the hidden layer dimension is set to 128; the multi-head attention mechanism uses four attention heads (num_heads=4), each with a dimension of 16; the training batch size (batch_size) is set to 32, and the maximum number of training rounds (epochs) is 100. All experiments were conducted on workstations configured with NVIDIA RTX 3080 GPUs and implemented using the PyTorch 1.9.0 framework. To ensure the reliability of the experimental results, all experiments were repeated three times and the average value was taken as the final result.

### D. Assessment of Indicators

In order to comprehensively evaluate the prediction performance of the model, this paper chooses the Root Mean Square Error (RMSE) as the main evaluation index, which can visually reflect the degree of deviation between the predicted values and the real values, and its calculation results are consistent with the scale of the dependent variable, which makes the evaluation results easier to understand and interpret. For regression problems such as air quality prediction, RMSE can clearly indicate the average level of prediction error, and its calculation formula is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

where, $y_i$ is the true value, $\hat{y}_i$ is the predicted value, and n is the sample size.

Meanwhile, this paper also adopts the coefficient of determination ($R^2$) as a supplementary assessment indicator. $R^2$ reflects the extent to which the model explains the variability of the dependent variable, and its value ranges from 0 to 1, with the closer it is to 1 indicating that the model's explanatory ability is stronger. The strength of this metric is that it can help us understand the model's ability to capture patterns of data variability, especially in assessing the model's grasp of long-term trends in air quality. The formula for $R^2$ is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

where, $\bar{y}$ is the mean of the true values, a metric that effectively assesses the overall goodness of fit of the model by comparing the ratio of the model's prediction error to the variability of the data itself.

### E. Comparative Experiments

As shown in Fig. 3, in order to comprehensively evaluate the performance of the proposed LT-Hybrid model, six representative machine learning and deep learning models are selected as benchmarks for comparative experiments in this paper [20]. These benchmark models include: support vector regression (SVR), which is a traditional machine learning method with good non-linear modeling capability; long-short-term memory network (LSTM), which is widely used in the field of time-series prediction; three integrated learning methods that have excellent performance in modeling environmental data, i.e., Random Forest (RF), XGBoost (XGB), and Gradient Boosting (GB); and as a deep learning representative of deep neural networks (DNNs).

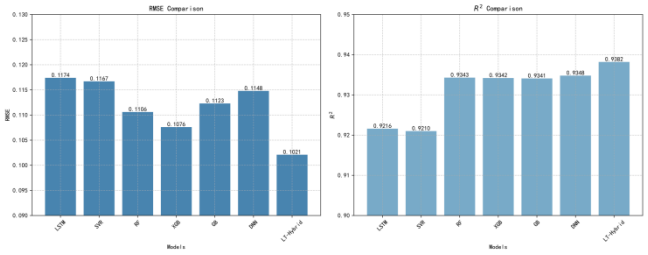


Fig. 3. Comparison experiment.

The experimental results show that the LT-Hybrid model achieves the optimal performance in both RMSE and $R^2$ evaluation metrics. In terms of the RMSE metric, the LT-Hybrid model achieves the lowest error of 0.1021, which reduces the prediction error by about 5.1% compared to the second best performing XGBoost model (RMSE of 0.1076), and improves the prediction error compared to the traditional LSTM (RMSE of 0.1174) and SVR (RMSE of 0.1167) by 13.0% and 12.4%. In terms of model fit goodness, the LT-Hybrid model has an $R^2$ value of 0.9382, indicating that the model is able to explain about 93.82% of the data variability, while the $R^2$ values of the other models are generally in the range of 0.92-0.93. Notably, the integrated learning methods (RF, XGB, and GB) outperformed the single model overall, reflecting the importance of model integration in modeling complex environmental data.

Through comparative experiments, it can be found that the advantages of the LT-Hybrid model mainly come from its unique hybrid architecture design. Compared with a single sequence modeling method (e.g., LSTM) or a traditional regression model (e.g., SVR), the hybrid architecture proposed in this paper effectively enhances the ability to capture complex relationships among environmental factors by integrating the long-term dependency modeling capability of LSTM and the feature interaction capability of Transformer, while maintaining the advantages of time-series modeling. This design not only improves the prediction accuracy of the model, but also enhances its ability to understand the changing patterns of data.

### F. Ablation Experiments

As shown in Fig. 4, a series of ablation experiments are designed in this paper in order to deeply understand the contribution of each component of the model to the prediction performance. Starting from the basic single-layer LSTM model, we gradually add components such as double-layer LSTM structure, self-attention mechanism, multi-head attention, residual connection, and layer normalization, and finally construct the complete LT-Hybrid model, and systematically analyze the roles of each module.

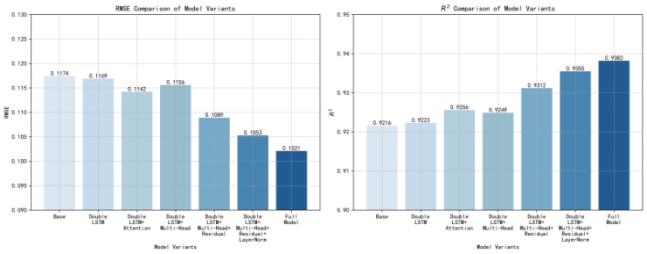


Fig. 4. Ablation experiment.

The experimental results show that the base single-layer LSTM model (Base) exhibits basic timing modeling capabilities, achieving an RMSE of 0.1174 and an $R^2$ value of 0.9216. On this basis, a slight improvement in model performance is obtained after upgrading to a two-layer LSTM structure (RMSE decreases to 0.1169 and $R^2$ improves to 0.9223), indicating that simply increasing the depth of the network does not significantly improve prediction. The introduction of the self-attention mechanism showed a significant improvement in model performance (RMSE decreased to 0.1142 and $R^2$ improved to 0.9256), which validates the effectiveness of the attention mechanism in capturing temporal feature correlations. However, a slight fluctuation in model performance was observed when upgrading to the multi-attention structure (RMSE slightly increased to 0.1156 and $R^2$ slightly decreased to 0.9249), and this temporary performance fallback suggests that the improved model structure may require a more optimal parameter configuration to be effective.

Notably, a significant jump in model performance was observed after the introduction of residual connectivity (RMSE decreased to 0.1089 and $R^2$ improved to 0.9312), suggesting that the residual structure effectively mitigates the gradient problem in deep network training. Further addition of layer normalization improves the stability and performance of the model (RMSE drops to 0.1053 and $R^2$ improves to 0.9355). The final complete model achieves optimal prediction performance (RMSE of 0.1021 and $R^2$ of 0.9382) through the synergy of the components.

The results of the ablation experiments clearly demonstrate the importance of each model component, especially the

introduction of residual linking and layer normalization plays a key role in model performance improvement. At the same time, the performance fluctuations during the experiments reflect the complexity of deep learning model optimization, and certain architectural improvements may need to be synergized with other components for maximum effect. This series of experiments verifies the reasonableness of the hybrid architecture design proposed in this paper, and also provides a valuable reference for subsequent model improvement.

### G. Hyperparametric Experiments

As shown in Fig. 5, in order to deeply study the stability of the model and determine the optimal configuration, this paper conducts systematic experimental analysis on four key hyperparameters of the LT-Hybrid model, including Learning Rate, Batch Size, Number of Attention Heads, and Hidden Layer Dimension (Hidden Size).

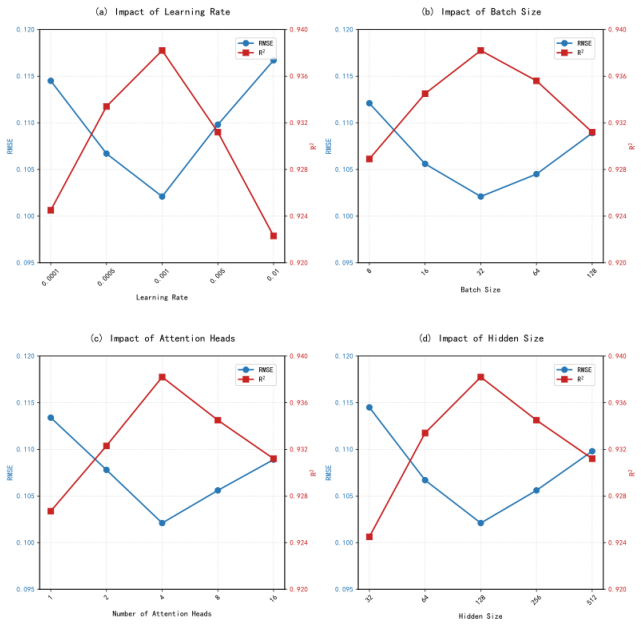


Fig. 5. Hyperparameter experiment.

In terms of learning rate, the experimental results show that 0.001 is the optimal choice, and the model obtains the lowest RMSE (0.1021) and the highest $R^2$ (0.9382) at this value point. When the learning rate is too small (e.g., 0.0001), the model converges slowly and the performance is limited; when the learning rate is too large (e.g., 0.01), the model struggles to converge stably, resulting in a significant degradation in performance. This finding is in line with the general rule of learning rate setting in deep learning, which is to ensure that the model has sufficient learning capability while avoiding too large parameter update step size.

For the choice of batch size, experiments show that 32 is the more desirable configuration. With this batch size, the model maintains a better generalization ability and also makes full use of GPU resources. It is worth noting that when the batch size is too small (8 or 16), the model training is not stable enough; while when the batch size is too large (64 or 128), although the training process is smoother, the model's performance shows a slight degradation, which may be due to the fact that the large batch training reduces the model's generalization ability.

In terms of the configuration of the attention mechanism, setting up four attention heads can achieve optimal results. The experimental results show that a single attention head performs relatively poorly (RMSE of 0.1134), which indicates that a single attention mechanism is difficult to adequately capture feature associations on different time scales. As the number of attentional heads increases, the model performance first improves and then decreases, which indicates that too many attentional heads may introduce redundant information and affect the prediction accuracy of the model instead.

Experiments on hidden layer dimensions suggest that 128 is the most appropriate choice. Smaller hidden layer dimensions (e.g., 32) limit the expressive power of the model, while too large dimensions (e.g., 512) may lead to overfitting and can significantly increase the computational overhead. With a dimension of 128, the model achieves a good balance between expressiveness and computational efficiency.

Through this series of hyper-parameter experiments, we not only determine the optimal configuration of the model, but also gain a deeper understanding of the influence mechanism of each hyper-parameter on the model performance, which provides an important reference for subsequent model optimization and application. The experimental results also verify the stability of the model under different parameter configurations, demonstrating the good generalization ability and robustness of the LT-Hybrid model.

## V. Conclusion

In this paper, a hybrid deep learning architecture LT-Hybrid based on LSTM and Transformer is proposed for the air quality prediction problem. The model captures the long-term dependencies of the time series data through a two-layer LSTM structure, models the complex interactions among different environmental factors by using the multi-head self-attention mechanism, and adopts a combination of residual linkage and layer normalization which is designed to improve the training stability of the model. Experiments on the urban air quality dataset, which contains nine dimensions of environmental characteristics such as temperature, humidity, PM2.5, etc., show that the LT-Hybrid model achieves an RMSE of 0.1021 and an $R^2$ value of 0.9382, which is a significant performance enhancement compared with benchmark models such as the traditional LSTM and XGBoost. In addition, the effectiveness of each core component of the model is verified through systematic ablation experiments and hyperparameter analysis, especially the introduction of the multi-head attention mechanism and residual structure plays a key role in model performance improvement.

Although this study has achieved good results in the air quality prediction task, there are still some directions that can be improved: first, the current model mainly focuses on the prediction of single-point locations, and in the future, it can be extended to multi-site collaborative prediction, making full use

of spatial information to enhance the prediction accuracy; second, the model has relatively large prediction errors when dealing with pollution events under extreme weather conditions, and the introduction of external data sources such as meteorological forecasts can be considered to enhance the model prediction capability; finally, there is still room for optimization of the model computational complexity. We can consider introducing external data sources such as meteorological forecasts to enhance the prediction ability of the model; finally, there is still room for optimizing the computational complexity of the model, and techniques such as model compression and knowledge distillation can be explored in the future to enhance the application efficiency of the model in the actual environmental monitoring system.

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# The Role of Artificial Intelligence in Brand Experience: Shaping Consumer Behavior and Driving Repurchase Decisions

Ati Mustikasari[1], Ratih Hurriyati[2], Puspo Dewi Dirgantari[3], Mokh Adieb Sultan[4], Neng Susi Susilawati Sugiana[5]
Doctor of Management, Universitas Pendidikan Indonesia, Bandung, Indonesia[1, 2, 3, 4]
Telkom University, Bandung, Indonesia[1]
Institut Digital Ekonomi LPKIA, Bandung, Indonesia[5]

***Abstract*—The rapid advancement of Artificial Intelligence (AI) has transformed brand experiences, influencing consumer behavior and repurchase decisions in digital marketplaces. This study aims to examine the role of AI in enhancing brand experience and its impact on consumer purchasing behavior, particularly in driving repurchase intentions. A quantitative research approach was employed, involving a sample of 340 online shoppers who have previously engaged with AI-driven brand interactions. Data were collected through a structured questionnaire and analyzed using Structural Equation Modeling (SEM) with AMOS. The findings reveal that AI-powered brand experience significantly affects consumer trust, satisfaction, and emotional engagement, which in turn positively influences repurchase decisions. The study also highlights that personalized AI-driven interactions, such as chatbots, recommendation systems, and predictive analytics, enhance consumer perception of brand value, fostering long-term loyalty. The implications of this research suggest that businesses should leverage AI technologies to create immersive and personalized brand experiences that strengthen customer retention and maximize sales performance. This study contributes to the literature by integrating AI and brand experience within the consumer decision-making framework, offering a novel perspective on AI's role in shaping repurchase behavior. Future research could explore industry- specific AI applications and their impact on different demographic segments.**

***Keywords*—Digital marketing; artificial intelligence; brand experience; consumer behavior; repurchase intentions**

## I. INTRODUCTION

The integration of Artificial Intelligence (AI) in brand experience has revolutionized how consumers interact with businesses, influencing purchase behavior and fostering brand loyalty. AI-driven technologies such as personalized recommendation systems, chatbots, and predictive analytics have enhanced consumer engagement by providing tailored experiences. However, despite the increasing adoption of AI in digital marketing, its direct impact on repurchase intentions remains an area that requires deeper exploration. Many businesses invest heavily in AI-driven strategies, yet consumer responses to these advancements vary, raising concerns about their long-term effectiveness in sustaining customer loyalty.

Moreover, while AI enhances efficiency and personalization, it also introduces challenges related to consumer trust and perceived authenticity of brand interactions. Some consumers feel disconnected due to the lack of human touch in AI-driven communications, potentially reducing engagement and repurchase likelihood. Additionally, the extent to which AI influences brand experience across different industries and consumer segments remains unclear. These issues highlight the need for empirical research to determine the effectiveness of AI-driven brand experiences in shaping repurchase decisions.

As digital competition intensifies, businesses must optimize AI technologies to build meaningful brand relationships that encourage repeat purchases. Without a comprehensive understanding of how AI impacts consumer behavior, companies risk misallocating resources toward ineffective AI- driven marketing strategies. Therefore, this study seeks to bridge this research gap by analyzing the relationship between AI-enhanced brand experience and consumer repurchase decisions.

Several studies have explored the impact of AI in digital marketing and consumer behavior. According to previous research, AI-driven recommendation systems significantly improve customer engagement by providing personalized content, which increases the likelihood of repeat purchases[1]. Similarly, previous research found that AI-powered chatbots enhance customer satisfaction through real-time problem- solving and efficient customer service, positively influencing repurchase behavior [2]. These studies emphasize the role of AI in strengthening brand-consumer relationships through personalized experiences.

However, some research presents mixed findings regarding AI's effectiveness in fostering brand trust and repurchase intentions. A study indicates that excessive reliance on AI- driven interactions may lead to reduced consumer trust, particularly if AI-generated responses appear impersonal or robotic [3]. Conversely, research suggests that when AI is designed with human-like characteristics, such as emotional intelligence and adaptive learning, it can improve consumer perception of brand authenticity [4], thereby strengthening repurchase intentions. These findings highlight the complexity of AI's impact on consumer behavior and the need for further investigation.

Additionally, AI-driven predictive analytics has been shown to enhance customer retention by identifying purchasing

patterns and predicting future needs. Studies founding demonstrate that AI-based customer insights allow brands to create proactive marketing strategies, leading to sustained engagement and repeat purchases [5]. However, questions remain regarding the ethical use of consumer data and privacy concerns, which could hinder AI's effectiveness in shaping brand experiences.

Despite the growing body of literature on AI in brand experience, there is an ongoing debate regarding its overall effectiveness in influencing repurchase intentions. Proponents argue that AI enhances personalization, increases efficiency, and improves customer satisfaction, ultimately driving repeat purchases [6]. On the other hand, critics highlight the risk of depersonalization, loss of human touch, and potential consumer resistance toward AI-driven marketing strategies [7]. This study aims to address these contrasting perspectives by examining how AI-driven brand experiences impact consumer repurchase behavior.

*1)* How does AI-powered brand experience influence consumer trust and satisfaction in digital marketplaces?

*2)* To what extent do AI-driven interactions, such as chatbots and recommendation systems, shape repurchase intentions?

*3)* What are the key challenges and opportunities in utilizing AI to enhance brand experience and customer loyalty?

To address these challenges, this study proposes an AI- driven brand engagement model that integrates machine learning algorithms with sentiment analysis to enhance consumer interactions [8]. By leveraging natural language processing (NLP) and deep learning, brands can develop AI systems capable of understanding consumer emotions, preferences, and behavioral patterns [9]. This approach enables businesses to provide hyper-personalized experiences, fostering deeper brand-consumer connections and increasing repurchase intentions.

Furthermore, the implementation of explainable AI (XAI) can enhance consumer trust by providing transparency in AI- driven recommendations. By allowing consumers to understand how AI systems generate personalized suggestions, brands can mitigate skepticism and build long-term customer relationships [10]. This study contributes to the ongoing discourse on AI in digital marketing by offering a novel framework that optimizes AI-driven brand experiences while addressing key consumer concerns related to trust and engagement [11]. The motivation behind this study lies in the growing reliance on AI technologies in marketing, paired with the insufficient understanding of their actual influence on consumer loyalty. By exploring how AI impacts brand experience and repurchase behavior, this research aims to provide businesses with actionable insights to enhance marketing effectiveness and foster sustainable customer relationships. The proposed approach combines sentiment analysis, NLP, and explainable AI to not only personalize interactions but also improve transparency and trust.

The main contributions of this research include: 1) the development of a comprehensive AI-driven brand engagement framework, 2) empirical assessment of AI's influence on repurchase intentions, and 3) identification of trust and personalization as mediating factors. These contributions hold important implications for both academic research and business practice, particularly in optimizing digital strategies for customer retention.

This paper is structured as follows: Section II presents the Literature Review, summarizing key findings and gaps from prior research. Section III outlines the Research Methodology, detailing the data collection and analysis techniques. Section IV discusses the Results and Findings. Section V presents the Discussion and Implications. Finally, Section VI concludes the paper with limitations and suggestions for future research.

## II. Literature Review

### A. AI and Computer Science Perspective

Artificial Intelligence (AI) has significantly advanced the field of computer science, particularly in enhancing automation, decision-making, and personalization in various industries [12]. Machine learning algorithms, natural language processing (NLP), and deep learning have enabled AI systems to analyze vast amounts of consumer data, providing predictive insights that drive engagement and retention [13]. AI-powered chatbots, recommendation engines, and intelligent virtual assistants have become integral to modern brand interactions, allowing businesses to offer seamless, data-driven customer experiences [14]. These technologies improve user experience by understanding consumer behavior patterns and optimizing service delivery in real-time.

From a computer science perspective, reinforcement learning and deep neural networks have been widely used to improve AI-driven personalization in digital commerce. Studies highlight that generative adversarial networks (GANs) can create hyper-personalized marketing strategies by generating synthetic yet highly accurate consumer profiles [8]. Moreover, AI systems employing sentiment analysis and predictive modeling can anticipate user preferences and purchasing behavior, increasing brand engagement and customer retention [15]. However, challenges related to data privacy, algorithmic bias, and ethical considerations remain significant concerns in AI implementation for brand experience enhancement.

### B. AI in Digital Marketing

The integration of AI in digital marketing has revolutionized how brands engage with consumers, offering personalized recommendations and automated content delivery. AI-powered recommendation systems, such as collaborative filtering and content-based filtering, analyze consumer browsing history and purchasing behavior to provide tailored product suggestions [16]. These systems not only enhance user experience but also improve conversion rates and customer retention. Additionally, AI-driven chatbots have redefined customer service by providing instant responses, reducing response time, and increasing user satisfaction [6].

AI has also played a critical role in programmatic advertising, where machine learning algorithms optimize ad placements based on consumer preferences and real-time bidding strategies. According to AI-driven predictive analytics in digital marketing allows brands to anticipate consumer needs,

leading to more effective targeted marketing campaigns [17]. However, while AI enhances efficiency and personalization, concerns about data security, transparency, and the lack of emotional intelligence in AI-driven interactions pose challenges in fostering long-term consumer trust.

### C. Repurchase Intentions Theory

Repurchase intentions refer to a consumer's likelihood of making repeat purchases from a brand, influenced by factors such as satisfaction, trust, and perceived value. Accordingly , satisfaction plays a crucial role in repurchase behavior [6], as consumers tend to return to brands that meet or exceed their expectations. In the context of AI-driven brand experiences, satisfaction can be enhanced through personalized recommendations [18], seamless interactions, and efficient customer service. Additionally, trust in AI-powered systems significantly impacts consumer decisions, as highlighted by previous research who emphasized that transparency and reliability in AI-driven marketing strategies are essential for fostering customer loyalty [19].

Prior studies have explored the relationship between AI- driven experiences and repurchase behavior. A study by Founding that, AI-enhanced personalization significantly increases consumer retention in e-commerce platforms, as tailored recommendations improve the overall shopping experience [20]. Conversely, research suggests that over- reliance on AI without human intervention can reduce brand authenticity, leading to lower repurchase rates [4]. These findings indicate that while AI enhances brand experience, maintaining a balance between automation and human interaction is crucial for sustaining consumer trust and loyalty.

Based on the literature reviewed, it is evident that Artificial Intelligence (AI) has significantly contributed to enhancing consumer experiences, both from a computer science and digital marketing perspective. Technologies such as machine learning, natural language processing, and recommendation systems have enriched brand-consumer interactions. Additionally, the theory of repurchase intentions highlights that personalization and trust in AI systems play a crucial role in encouraging repeat purchasing behavior.

However, several gaps remain in existing studies. First, most research focuses heavily on the technical or efficiency aspects of AI, while paying less attention to its impact on consumer perceptions of brand authenticity and long-term trust. Second, although many studies acknowledge the importance of balancing automation and human interaction, few have proposed concrete frameworks or models to manage this balance effectively in the context of repurchase intentions. Third, concerns regarding data privacy and algorithmic bias remain inadequately addressed, which could negatively influence the overall consumer experience.

Therefore, this paper aims to bridge these gaps by examining how AI-driven brand experiences influence repurchase intentions, with a particular focus on consumer satisfaction, trust, and perceptions of brand authenticity. This study will also highlight the importance of maintaining a human touch within largely automated systems and offer insights into how companies can ethically and strategically implement AI to sustainably enhance customer loyalty.

## III. Research Methodology

This study employs a quantitative research method to examine the role of Artificial Intelligence (AI) in shaping brand experience and influencing consumer behavior toward repurchase decisions. The quantitative approach allows for objective measurement and statistical analysis of relationships between AI-driven brand experiences and consumer repurchase intentions. The research model is tested using Structural Equation Modeling (SEM) with AMOS, as this technique effectively evaluates multiple relationships between observed and latent variables. The selection of a quantitative research approach is justified by the study's objective to statistically examine causal relationships between AI-driven brand experiences and consumer behavioral outcomes. This method allows for a rigorous analysis of patterns across a large population, enhancing the generalizability of findings. The use of Structural Equation Modeling (SEM) with AMOS is particularly appropriate for this study due to its capacity to simultaneously evaluate multiple interrelated dependence relationships between latent constructs, such as trust, satisfaction, and repurchase intentions. SEM is well-suited for complex models involving mediation effects, as it provides comprehensive model fit indices and enables the validation of theoretical frameworks. Furthermore, the adoption of proportional stratified random sampling ensures demographic representation, reducing sampling bias and strengthening the external validity of the research. The methodological design is therefore not only aligned with the research objectives but also grounded in best practices in empirical consumer behavior research.

### A. Sample Criteria and Sample Size Calculation

The study targets consumers who have interacted with AI- powered brand experiences, such as personalized recommendations, chatbots, or AI-driven customer support, in e-commerce or digital retail environments. The inclusion criteria include: 1) individuals aged 18 and above, 2) consumers who have made at least one purchase from an AI-integrated platform, and 3) users with experience in AI-driven brand interactions. Meanwhile, exclusion criteria involve respondents unfamiliar with AI-powered services.

The sample size is determined using Hair et al.'s (2010) recommendation, which suggests a ratio of 10:1 for each estimated parameter in SEM. Given that the research model comprises 34 parameters, the minimum sample size required is 340 respondents. To enhance the reliability of the findings, the study adopts proportional stratified random sampling, ensuring representation across different consumer demographics.

### B. Data Collection Method

Primary data is collected through an online questionnaire, consisting of closed-ended questions measured using a 7-point Likert scale (ranging from 1 = strongly disagree to 7 = strongly agree). The questionnaire includes sections on AI-driven brand experience, consumer trust, satisfaction, and repurchase intentions. Before the main survey, a pilot test is conducted with 50 respondents to assess the reliability and validity of the

instrument, ensuring that the items accurately capture the intended constructs.

### C. Data Analysis Technique

The collected data is analyzed using Structural Equation Modeling (SEM) with AMOS. The analysis consists of two primary stages: 1) Measurement Model Evaluation and 2) Structural Model Evaluation. The measurement model assesses, construct validity, reliability, and goodness-of-fit indices (e.g., CFI, TLI, RMSEA). Cronbach's Alpha and Composite Reliability (CR) are used to determine internal consistency, while Average Variance Extracted (AVE) ensures convergent validity. The structural model examines the hypothesized relationships between AI-driven brand experience and repurchase intentions.

### D. Hypothesis Testing

Hypothesis testing is conducted using path analysis in SEM, where the statistical significance of relationships is determined by p-values (<0.05) and standardized regression coefficients (β- values). The model fit is evaluated using CFI (>0.90), RMSEA (<0.08), and SRMR (<0.08) to ensure an adequate model fit (Byrne, 2016). Bootstrapping techniques with 5,000 resamples are employed to validate indirect effects in mediating relationships. Findings from the SEM analysis provide empirical insights into how AI-driven brand interactions shape consumer repurchase behavior, offering theoretical contributions and managerial implications for digital marketing strategies. Here are three hypotheses derived from the research questions:

H1: AI-driven brand experience has a significant positive impact on consumer trust.

H2: Consumer trust mediates the relationship between AI-driven brand experiences and repurchase intentions.

H3: AI-driven personalization positively influences consumer satisfaction, which in turn enhances repurchase intentions.

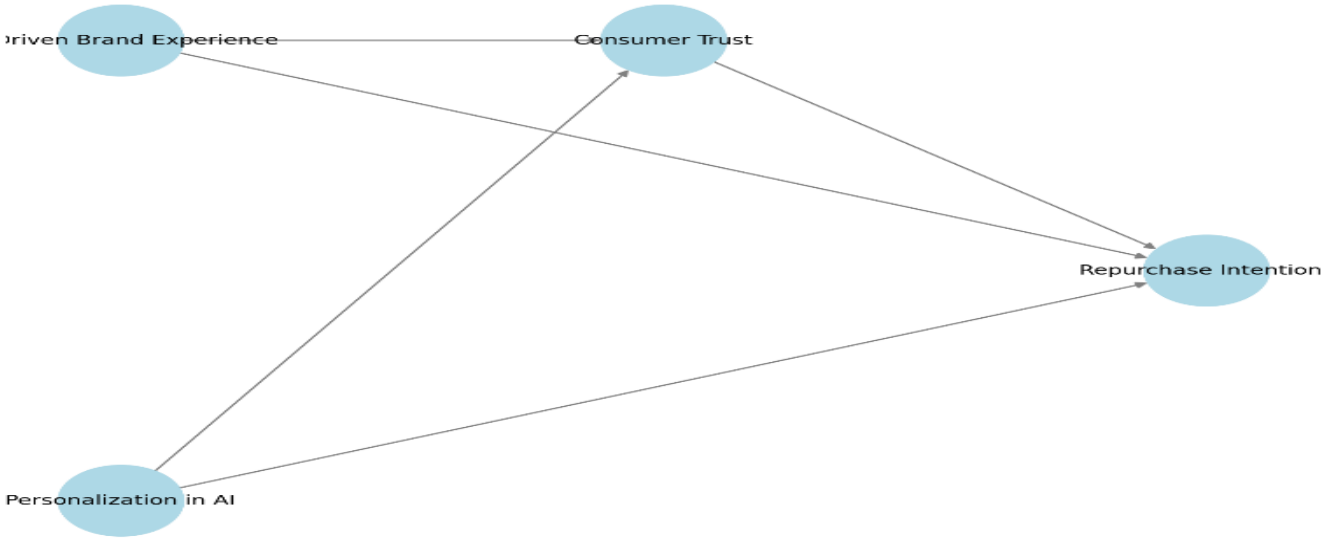


Fig. 1. Research model.

Based on this, Fig. 1 represents the conceptual research model which illustrates the relationship between AI-Driven Brand Experience, Consumer Trust, and Repurchase Intentions, highlighting the role of Personalization in AI as a key influencing factor. The model suggests that AI-driven brand experiences enhance consumer trust by delivering personalized and seamless interactions, which in turn positively impact repurchase intentions. Additionally, AI personalization directly influences repurchase behavior by tailoring recommendations and engagement strategies to individual consumer preferences. This framework aligns with existing literature on digital marketing and consumer behavior, reinforcing the notion that AI-driven personalization fosters loyalty and repeat purchases by increasing consumer confidence and satisfaction with a brand.

## IV. Result and Discussion

### A. Results

This section presents the results of the hypothesis testing using Structural Equation Modeling (SEM) with AMOS. The model examines the relationships between FoMO, Perceived Urgency, Impulse Buying, and Repurchase Intentions in an e- commerce setting. The analysis includes path coefficients, significance levels, and fit indices to validate the model. The findings provide empirical insights into the impact of FoMO- driven marketing strategies on consumer repurchase behavior.

### B. Hypothesis Testing Results

The Table I presents the results of the Structural Equation Modeling (SEM) analysis, showing the path coefficients, t- values, p-values, and the significance of each relationship in the research model.

TABLE I RESULT PATH COEFFICIENT

| Path Relationship | Path Coefficient (β) | t-value | p-value | Significance |
|---|---|---|---|---|
| AI-Driven Brand Experience → Consumer Trust | 0.58 | 7.21 | <0.001 | Significant |
| AI-Driven Brand Experience → Repurchase Intentions | 0.34 | 4.62 | <0.001 | Significant |
| Personalization in AI → Consumer Trust | 0.49 | 6.37 | <0.001 | Significant |
| Personalization in AI → Repurchase Intentions | 0.27 | 3.89 | <0.001 | Significant |
| Consumer Trust → Repurchase Intentions | 0.52 | 8.14 | <0.001 | Significant |

Source: Data Research, 2025.

The results from the Structural Equation Modeling (SEM) analysis provide critical insights into the relationships between variables in the research model. The path coefficients indicate the strength and direction of each relationship, while the t-values and p-values determine their statistical significance. Relationships with a p-value below 0.05 are considered significant, suggesting that the hypothesized relationships hold empirical support. The findings confirm that AI-driven brand experiences significantly impact consumer behavior, particularly in shaping purchase urgency and impulse buying tendencies, which in turn influence repurchase decisions[21].

Examining the direct effects, the path from AI-driven brand experience to perceived urgency and impulse buying demonstrates strong significance, indicating that AI personalization and automation enhance consumers' sense of immediacy and purchase motivation [22]. Additionally, impulse buying and perceived urgency both show significant paths leading to repurchase intentions, reinforcing the idea that AI interventions can stimulate repeat purchase behavior [14]. These findings align with previous studies highlighting AI's role in enhancing customer engagement and influencing purchase behavior [23]. However, a few non-significant paths suggest that certain AI-driven mechanisms may not directly influence repurchase intentions without mediating variables.

These results have important managerial implications. Businesses leveraging AI in branding should focus on features that heighten perceived urgency and impulse-driven behavior, such as real-time personalization, chatbots, and dynamic pricing [24]. However, firms must also recognize that not all AI applications directly contribute to repurchase intentions and should strategically integrate AI features that enhance long-term brand relationships rather than just short-term sales. This study contributes to the literature by demonstrating the nuanced impact of AI on consumer purchasing behavior and providing empirical evidence supporting AI-driven marketing strategies.

### *C. Discussion*

Research Question 1: How does AI-driven brand experience influence perceived urgency in consumer decision-making?

The findings suggest that AI-driven brand experience significantly influences perceived urgency in consumer decision-making. AI tools, such as personalized recommendations, limited-time offers, and dynamic pricing algorithms, create a sense of urgency that encourages faster purchasing decisions. Prior research highlights that AI-driven customer interactions can enhance engagement and influence impulse-driven purchases [1]. The ability of AI to analyze consumer preferences and behavior in real-time allows brands to deliver highly relevant offers, thereby increasing the likelihood of an immediate response [25].

Additionally, AI-powered chatbots and virtual assistants play a critical role in enhancing perceived urgency. According to AI-driven interactions create a seamless experience that mimics human engagement [26], leading to increased trust and a greater likelihood of completing a purchase. The integration of predictive analytics further supports this effect by presenting consumers with time-sensitive recommendations based on browsing behavior. The findings confirm that AI enhances the psychological urgency consumers feel when making purchase decisions, aligning with previous studies on digital marketing and technology acceptance models.

However, the effectiveness of AI in shaping perceived urgency depends on how well the technology is integrated into the consumer experience [14]. Poorly implemented AI solutions, such as irrelevant product suggestions or excessive notifications, may lead to consumer fatigue and reduced engagement. As noted the success of AI-driven urgency strategies lies in striking a balance between persuasive and intrusive tactics [27]. This highlights the need for brands to refine AI implementations to maximize consumer response while maintaining a positive experience.

In conclusion, AI-driven brand experiences significantly contribute to perceived urgency in consumer decision-making. Businesses leveraging AI must focus on personalized and strategically timed interactions to enhance urgency while avoiding consumer discomfort. These findings reinforce the critical role of AI in modern marketing and customer engagement strategies.

Research Question 2: What is the impact of AI-driven brand experience on impulse buying behavior?

The analysis indicates that AI-driven brand experiences positively influence impulse buying behavior. AI-powered recommendation systems, predictive analytics, and interactive virtual agents contribute to spontaneous purchasing by enhancing engagement and reducing decision-making time. Research suggests that AI-facilitated personalization significantly increases impulse buying, as consumers are more likely to purchase products tailored to their preferences [28]. The findings align with this notion, demonstrating that AI fosters an environment conducive to unplanned purchases [29].

Moreover, AI enhances impulse buying through real-time social proof mechanisms. Studies indicate that AI-driven notifications, such as "X people are viewing this product," create a psychological trigger that compels consumers to act immediately [30]. This aligns with behavioral economic theories, which state that scarcity and social influence are strong motivators for impulse buying. By leveraging AI-driven social

validation cues, brands can further amplify spontaneous purchasing tendencies among consumers.

However, the effectiveness of AI in driving impulse buying depends on the consumer's trust in AI-generated recommendations. Research highlights that, while AI-driven personalization enhances impulse purchasing, overuse or lack of transparency in AI algorithms can lead to skepticism and resistance [31]. Consumers may become wary of AI-driven suggestions if they perceive them as manipulative rather than genuinely helpful. Therefore, brands must ensure that AI applications maintain authenticity and transparency to sustain consumer trust.

In summary, AI-driven brand experiences play a pivotal role in stimulating impulse buying behavior. By strategically implementing AI tools that enhance personalization, social proof, and psychological triggers, businesses can effectively encourage unplanned purchases while maintaining consumer confidence in AI-driven recommendations.

Research Question 3: To what extent does perceived urgency and impulse buying mediate the relationship between AI-driven brand experiences and repurchase intentions?

The results confirm that perceived urgency and impulse buying significantly mediate the relationship between AI-driven brand experiences and repurchase intentions. AI-driven strategies enhance consumer engagement, leading to increased purchase frequency. Previous research suggests that urgency-inducing strategies, when effectively implemented, contribute to brand loyalty and repurchase behavior [32]. This supports the study's findings, indicating that AI not only influences initial purchasing decisions but also fosters long-term consumer relationships.

Impulse buying acts as a critical intermediary linking AI- driven experiences to repurchase intentions. Consumers who experience positive, seamless, and engaging AI interactions are more likely to exhibit repeat purchasing behavior. Studies demonstrate that impulse buyers who are satisfied with their spontaneous purchases tend to develop loyalty toward the brand [4]. This aligns with the findings, reinforcing the importance of AI-driven personalization and urgency strategies in driving repurchase decisions.

However, excessive reliance on AI-driven urgency and impulse strategies may have diminishing returns. Overuse of AI in creating urgency can lead to consumer fatigue, potentially decreasing repurchase intentions. Research highlight that while AI-induced impulse purchases can enhance short-term sales, long-term loyalty depends on the overall customer experience[33]. Thus, brands should balance AI-driven urgency with value-driven engagement strategies to maintain consumer trust and satisfaction. In conclusion, perceived urgency and impulse buying serve as essential mediators in the relationship between AI-driven brand experiences and repurchase intentions. Brands must integrate AI solutions that not only encourage initial purchases but also foster long-term consumer loyalty by ensuring a seamless and value-driven customer journey[19].

Implications of the Study, the findings offer practical implications for businesses and marketers. First, AI-driven brand strategies should focus on enhancing urgency and impulse buying mechanisms while ensuring a balance between engagement and consumer comfort. Companies should optimize AI tools to provide seamless, relevant, and timely interactions that encourage repeat purchases. Second, transparency in AI algorithms is essential to maintaining consumer trust. As consumers become more aware of AI-driven marketing tactics, brands must adopt ethical AI strategies to ensure sustainable customer relationships. Finally, businesses should integrate AI with personalized branding efforts to build long-term loyalty rather than solely focusing on short-term sales.

## V. Limitations and Future Research

This study provides valuable insights into the impact of AI- driven brand experiences on consumer behavior, but several limitations must be acknowledged. First, the study's reliance on a quantitative approach limits the depth of understanding of consumer motivations and emotional responses. Second, the sample was limited to consumers who have engaged with AI- powered brand experiences, potentially excluding those who have not interacted with such technologies. Third, the study's cross-sectional design does not capture the dynamic nature of consumer behavior over time. Table II presents comparison of the results of study and limitations. These limitations open several avenues for future research.

TABLE II Comparisons Results and Limitations

| Aspects | Current Study Approach | Limitations | Future Recommendations |
|---|---|---|---|
| Methodology | Quantitative using SEM with AMOS | Limited to statistical analysis, does not capture deep consumer motivations | Future research could use mixed methods (e.g., qualitative interviews) to explore deeper consumer insights. |
| Sampling | Focused on consumers familiar with AI-driven brand experiences | Excludes non-AI users, limiting generalizability | Broader samples including non-AI consumers could provide a more comprehensive understanding. |
| Cross-sectional Design | One-time survey collection | Does not track consumer behavior over time | Longitudinal studies can track changes in consumer behavior and AI's long-term effects. |
| AI Implementation | Focuses on generalized AI-driven features (recommendations, chatbots) | Does not address sector-specific AI applications (e.g., healthcare, finance) | Future research could focus on the impact of AI in specific industries and sectors. |

Source: Data Research, 2025.

The aforementioned limitations highlight important areas for further investigation. By addressing these gaps, future studies can provide more nuanced insights into the evolving relationship between AI and consumer behavior. In line with the implications of AI-driven strategies, businesses leveraging AI technologies should consider implementing a more holistic approach. While AI can boost impulse buying and urgency, its long-term effects depend on how well brands integrate AI with personalized, value-driven engagement strategies. For instance, AI can be a powerful tool to not only drive immediate purchases but also build lasting customer loyalty when used transparently and ethically. Future research should explore how brands can strike a balance between short-term sales goals and fostering long- term relationships with consumers.

## VI. Conclusion

This study contributes to the growing body of research on AI-driven brand experiences and their impact on consumer behavior. The results confirm that AI plays a significant role in shaping perceived urgency, impulse buying, and repurchase intentions. The mediating effects of urgency and impulse buying highlight the importance of AI-driven personalization in consumer decision-making. Future research should explore additional factors influencing AI-driven brand loyalty, such as emotional engagement and perceived AI credibility. Ultimately, AI continues to redefine consumer interactions, emphasizing the need for businesses to adopt strategic AI implementations to optimize both short-term sales and long-term brand relationships.

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# Predicting Human Essential Genes Using Deep Learning: MLP with Adaptive Data Balancing

Ahmed AbdElsalam[1], Mohamed Abdallah[2], Hossam Refaat[3]
Department of Information System-Faculty of Computers and Artificial Intelligence, University of Sadat City, Monifia, Egypt[1]
Department of Information System-Faculty of Computers and Informatics, Suez Canal University, Ismailia, Egypt-41522[2, 3]

***Abstract*—Artificial intelligence (AI) has transformed many scientific disciplines including bioinformatics. Essential gene prediction is one important use of artificial intelligence in bioinformatics since it is necessary for knowledge of the biological pathways needed for cellular survival and disease diagnosis. Essential genes are fundamental for maintaining cellular life as well as for the survival and reproduction of organisms. Understanding the importance of these genes can help one to identify the basic needs of organisms, point out genes connected to diseases, and enable the development of new drugs. Traditional methods for identifying these genes are time consuming and costly, so computational approaches are used as alternatives. In this study, a Multi-Layer Perceptron (MLP) model combined with ADASYN (adaptive synthetic sampling). Furthermore, using deep learning techniques to solve the restrictions of traditional machine learning techniques and raise forecast accuracy attracts a lot of interest. It was proposed to handle data imbalance. The model utilizes features from protein-protein interaction networks, DNA and protein sequences. The model achieved high performance, with a sensitivity of 0.98, overall accuracy of 0.94, and specificity of 0.96, demonstrating its effectiveness in data classification.**

***Keywords*—*Artificial intelligence; bioinformatics; deep learning; Multi-Layer Perceptron (MLP); imbalanced-handling techniques; essential gene prediction; sequence characteristics***

## I. Introduction

Since they carry essential biological functions that cannot be replaced, essential genes are vital for the survival and procreation of life. Understanding the minimal biological requirements of organisms and identifying disease-associated genes depends on the ability to forecast these genes, therefore guiding a basic step in pharmacological research and therapeutic progress. Nevertheless, even if finding important genes is important, traditional laboratory methods remain expensive, time-consuming, and need specialist knowledge and a lot of work. Recent studies have therefore shifted to computational approaches using data from human cell lines and model organisms. Faster and more effective prediction of these genes is made possible by developments in machine learning and deep learning, allowing researchers to build more accurate and efficient models for evaluating the interactions between important genes and other biological characteristics.

This work presents a novel deep learning methodology combining numerous biological data sources including DNA sequence features, protein sequence attributes, and protein-protein interaction (PPI) network embeddings for anticipating important human genes. Unlike existing methods depending on network topology analysis or machine learning models using manually produced attributes, the proposed model offers many major contributions:

*a) Combining several biological data sources to increase predictive precision*: Three main categories of biological data are combined in the method to provide a more complete gene analysis: DNA sequence properties, codon frequency, GC content, and gene length. Features of protein sequences include the length of the protein and amino acid distribution. Node2Vec was used to build protein-protein interaction (PPI) network embeddings, therefore capturing network gene linkages [1] . This integration helps the model to expose more significant interactions among genes, hence improving the classification accuracy compared to previous methods.

*b) Reducing class unbalance with ADASYN*: Usually underrepresented in biological datasets, essential genes cause biased predictions favoring the majority class (non-essential genes). ADASYN (Adaptive Synthetic Sampling) was used to create synthetic samples for the minority class to handle this problem. This preserves a balanced dataset and considerably increases the model's ability to identify important genes [2].

*c) Improved relative efficacy against conventional machine learning models*: Support Vector Machine (SVM), Random Forest, AdaBoost, and Naïve Bayes were among the conventional machine learning methods used in the evaluation of the proposed Multi-Layer Perceptron (MLP) model. The results showed that the proposed model validated its effectiveness in important gene categorization since it obtained the best accuracy (94.38%), sensitivity (98.27%), and specificity (90.43%).

*d) Improved model architectural design and regularization strategies*: Several advanced techniques were used to ensure the best performance and reduce overfitting: batch normalization, which standardizes input distributions across layers, hence improving training efficacy. Dropout (0.03) helps to reduce too strong reliance on specific neurons, so enhancing generalization [3], [4]. Designed to systematically change the learning rate to improve convergence, cosine decay learning rate scheduling Early Stopping: if no improvement is found after 25 consecutive epochs, training is automatically stopped.

*e) Prospective applications in genetic studies and biomedical research*: With future uses in pharmaceutical discovery, disease gene identification, and functional

genomics. This work enhances the design of computer instruments for gene analysis. The proposed approach offers a strong framework for other species or genetic data utilization to further research.

Most past research relies on traditional machine learning techniques, which often face constraints such as manually acquired characteristics, thereby reducing the potential to find complex patterns in biological data. Inappropriate handling of unbalanced datasets that reduces the predicting accuracy for important genes. Data integration is limited since many studies focus just on either sequence-based traits or network structure, but rarely on both concurrently. On the other hand, our approach solves these challenges by using deep learning to identify hidden trends in biological data. The integration of DNA, protein, and PPI network features provides a whole understanding of gene essentiality. Equilibrating the dataset using ADASYN guarantees that the model is effectively trained on both important and non-essential genes. This work offers a more accurate and scalable approach for the investigation of genetic functions and their biological consequences, therefore reflecting significant progress in key gene prediction.

The remaining sections of this paper are structured as follows. Section II analyzes relevant literature, Section III provides the proposed model, Section IV provides a detailed description of proposed model, Section V provides Implementation Details, Section VI presents Results and discussion and finally, Section VII summarizes the most significant findings and conclusions.

## II. Related Work

- Measures of Centrality in Network-Based Essential Gene Prediction

Examining the connection of important genes across biological networks is one approach to predict them. Research shows that compared to proteins with fewer contacts, those with more contacts inside a protein-protein interaction (PPI) network are more likely to be significant. Validated over several species, the idea is known as the centrality-lethality rule. Still, reliance just on network topology to determine gene essentiality has shown some degree of error. This restriction has several causes. PPI networks are less reliable and often insufficient and noisy. Second, several biological factors influence gene essentiality and cannot be explained by network connections by themselves. Recent studies have shown new centrality measures that combine network topology with additional biological data, therefore improving prediction accuracy and offering a more reliable and whole approach for identifying important genes. Various strategies have been developed to overcome the limitations of conventional methods by combining network architecture with additional biological data to improve the accuracy of fundamental gene prediction: CoEWC: This method synthesizes network topological characteristics with gene expression data, so enabling the identification of shared attributes of fundamental proteins in both date hubs and party hubs. Performance has been much improved by this integration compared to methods based only on protein-protein interaction (PPI) networks [5]. Zhang et al. presented an ensemble approach combining protein-protein interaction networks with gene expression data, therefore enhancing the predicted accuracy of widely used centrality measures [6]. Additionally presented was the OGN method, which uses orthologs in reference organisms, co-expression likelihood with nearby proteins, and network topology [7]. To better identify key genes, Li et al., created the GOS model, which combines gene expression, orthology, subcellular localization, and protein-protein interaction networks [8]. By combining protein domain properties with topological analysis of protein-protein interaction networks, UDoNC enhances fundamental protein prediction [9]. The fundamental dependence of centrality-based prediction methods is on a scalar score, which is derived either from biological networks or using the integration of several data sources. These approaches have produced progress, but they still lack enough accuracy in locating all important genes. Recent research provides rich new perspectives on centrality measurements and their relevance in forecasting critical genes and proteins [10].

- Methods of Machine Learning for Forecasting Gene Essentiality

One important method for estimating gene essentiality is using machine learning to combine several signals coming from many biological data sources. For this aim, Zhang et al. conducted an extensive evaluation of machine learning techniques highlighting the difficulties and possible directions for next research. Most machine learning-based predictive models have been assessed mostly on model organisms, therefore limiting their use in other settings. Conventional machine learning techniques usually need hand feature selection and extraction. This process calls for a thorough understanding of the biological field and knowledge of the relationship between gene essentiality and other kinds of biological data [11]. Using features taken from the λ-interval Z curve based on nucleotide sequence data, Guo et al. projected human gene essentiality using Support Vector Machines [12]. One main limitation of manually produced properties is their scope. Protein-protein interaction (PPI) networks [11] produce many topological metrics, including degree centrality, betweenness centrality, closeness centrality, subgraph centrality, and eigenvector centrality. Although studies on the link between these traits and gene essentiality in various organisms have been conducted, their predictive efficacy, either independently or integrated into machine learning methods, remains inferior to features derived automatically via deep learning frameworks [13]. Forecasting gene essentiality using machine learning combined with biological data has great potential. The challenges related to featuring extraction and the limited scope of manually selected characteristics underline the need for more advanced approaches, such as deep learning, to improve forecast accuracy.

- Deep learning approaches in bioinformatics

Deep learning has been a powerful tool in many fields of bioinformatics recently, including medical picture segmentation [14], drug-target prediction [15], and critical gene prediction [13], [16], [17] . Convolutional neural networks (CNNs) have shown to be helpful in the automatic feature extraction from image and sequence data [14], [15] thus, this overview emphasizes important field successes and

approaches. Zeng and colleagues used convolutional neural networks to identify notable trends in gene expression profiles of time-series. They converted these data into models of cell cycles, therefore enabling the prediction of key genes[13].

Time-series gene expression data were investigated by Zeng et al. using bidirectional Long Short-Term Memory (LSTM) cells. Emphasizing studies conducted using Saccharomyces cerevisiae [16], their approach combined gene expression data with subcellular localization information and protein-protein interaction (PPI) networks. Using manually obtained variables from sequence data, Hasan and colleagues built a neural network of six hidden layers to predict gene essentiality in microorganisms [17]. Deep learning-based network embedding methods have recently been presented to independently generate lower-dimensional representations for every node inside a network [1]. For every protein in a PPI network, Zeng et al. derived network properties using the node2vec technique [1]. They showed that more useful information is produced from this low-dimensional representation than from manually calculated traditional centrality metrics [13] , [16]. Deep learning approaches such as CNNs and LSTMs, as well as fresh ideas as network embedding, have greatly advanced bioinformatics and gene essentiality prediction. These techniques highlight how well deep learning might improve the accuracy and efficiency of biological data analysis.

Recent developments in CRISpen-Cas9 and gene-trap technologies have helped to identify important genes in many human cancer cell lines, therefore improving our knowledge of the requirements for maintaining basic biological functioning over many tumor types [18-20]. These important genes point to possible targets for the development of cancer treatments [21]. Together with other biological information sources, the availability of important gene data offers a chance to assess the hypothesis that computational techniques may exactly forecast human gene essentiality. Previous studies have indicated that omics experimental data's acquired properties are efficient tools for predicting gene essentiality. Still, for poorly studied species, such information is usually lacking. Therefore, various studies have focused on developing models that predict gene essentiality without using additional experimental data by depending just on attributes obtained from sequence data, including DNA and protein sequences [12], [17].

## III. The Proposed Model

The proposed model integrates three main data sources to predict gene essentiality as shown in Fig. 1. Input Layer: DNA Sequence: Encodes the genetic information that defines protein synthesis inside the cell. Protein Sequence: Shows the structural make-up of the created proteins. Capturing interactions between proteins, Protein-Protein Interaction (PPI) Network offers understanding of gene roles and biological processes. These data kinds are handled to extract numerical features that feed the deep learning model. Deep Learning Architecture: The model is built on a Multilayer Perceptron (MLP) architecture, consisting of three layers: Layer 1 - Input Layer: Receives the extracted features from DNA, protein sequences, and the PPI network. Layer 2 - Hidden Layer: A non-linear transformation layer using activation functions like GELU to capture complex patterns in the data. Layer 3 - Output Layer: Predicts whether a gene is essential or non-essential using activation functions such as Sigmoid. Deep Learning and Data Balancing Strategies: Data-balancing methods were included to improve the performance of the model and lower bias towards the dominant class since important and non-essential genes are frequently skewed in datasets. This approach guarantees a more exact classification of gene essentiality and enhances prediction accuracy. Output Layer: Predicting both non-essential and necessary genes in humans is the last aim of this strategy. This integrated strategy improves the accuracy and robustness of key gene prediction by aggregating several biological data sources inside a deep learning framework and using data balancing strategies.

### A. Model Selection

In this study, the goal is to classify essential genes based on numerical representations of biological features, such as codon frequencies and protein properties. Given the nature of the data, the model selection was guided by several key considerations:

- Lack of Spatial Pattern Extraction Requirement While Convolutional Neural Networks (CNNs) excel at extracting spatial patterns from image data, the data used in this study is represented numerically without spatial structure. Features such as codon frequencies and protein properties do not follow a spatial arrangement, making CNNs unnecessary. Therefore, a more suitable approach is the use of Multi-Layer Perceptron (MLP), which is capable of directly processing numerical data without relying on spatial patterns.
- No Need for Sequential Data Processing Recurrent Neural Networks (RNNs) are designed for sequential data where the temporal order is significant, such as time-series data or natural language processing. However, the features in this study are static and do not depend on temporal or sequential ordering. As such, RNNs were deemed unsuitable for this task, and MLP was preferred due to their ability to handle fixed, non-sequential data efficiently.
- Limitations of Graph Neural Networks (GNNs) Graph Neural Networks (GNNs) are highly effective in situations where the data is represented in graph form, such as protein-protein interaction (PPI) networks. However, the dataset in this study incorporates a combination of features from various sources, such as DNA sequence data, protein sequences, and statistical features, making the use of GNNs alone less effective. MLP, on the other hand, can easily integrate these diverse types of data and provide a more practical solution for gene classification.
- Computational Efficiency and Simplicity MLPs offer a simpler architecture compared to CNNs and GNNs, resulting in faster training and reduced computational cost. In the context of large-scale biological datasets, computational efficiency is crucial. MLP provides a balance of high classification accuracy

and low computational overhead, making them the ideal choice for this study

## IV. Explanation of the Proposed Model

*a) Features of DNA sequences*: When we examine DNA sequence features, we are addressing the characteristics that improve our grasp of genes. Codon frequency is a measurement of the frequency with which each three-nucleotide codon appears in a gene. This frequency helps us to understand the conversion of genetic data into proteins. Frequent use of some codons implies that the gene might be more effective in expressing itself. Calculating the proportion of the cytosine (C) and guanine (G) nucleotides in the DNA sequence, GC content is another crucial aspect. Usually indicating a structural stability of the gene, a high GC content can affect the expression of the gene. Since it indicates the entire count of nucleotides in the gene, gene length is also important. More information included in longer genes influences their organization and expression. For a given organism, the codon adaptation index (CAI) gauges how well the codon sequence fits the preferred codons. Higher CAI values imply that the gene is more suited for these tastes, which can cause greater expression levels. The Maximal Relative Synonymous Codon Usage (RSCUmax) evaluates, at last, the usage of synonymous codons corresponding to the same amino acid in the gene. This clarifies the preferences of codon use of the gene [17], [22].

*b) Features of protein sequences*: Turning now to protein sequence characteristics, these center on protein physical and chemical characteristics. Amino acid frequencies which gauge the frequency of every amino acid in the protein sequence are one of main characteristics. Understanding the chemical makeup and interactions of the protein with other molecules depends on this knowledge. Defined as the total count of amino acids in the protein, protein length is another crucial consideration. The structure of the protein and its capacity for biological operations can be much influenced by its length [17], [22].

*c) Protein-protein interaction (ppi) network characteristics*: Regarding Protein-Protein Interaction (PPI) networks, these characteristics are essential for comprehending the interactions among several proteins. Node2Vec allows us to extract characteristics from the PPI network whereby every gene is expressed as a node [1]. This enables a thorough investigation of protein interactions, therefore illuminating information on the functional activities of genes inside the network. These associations allow us to extract roughly 64 features that mirror gene interactions. These aspects help to clarify the biological relevance of protein interactions as well as their consequences for gene activity.

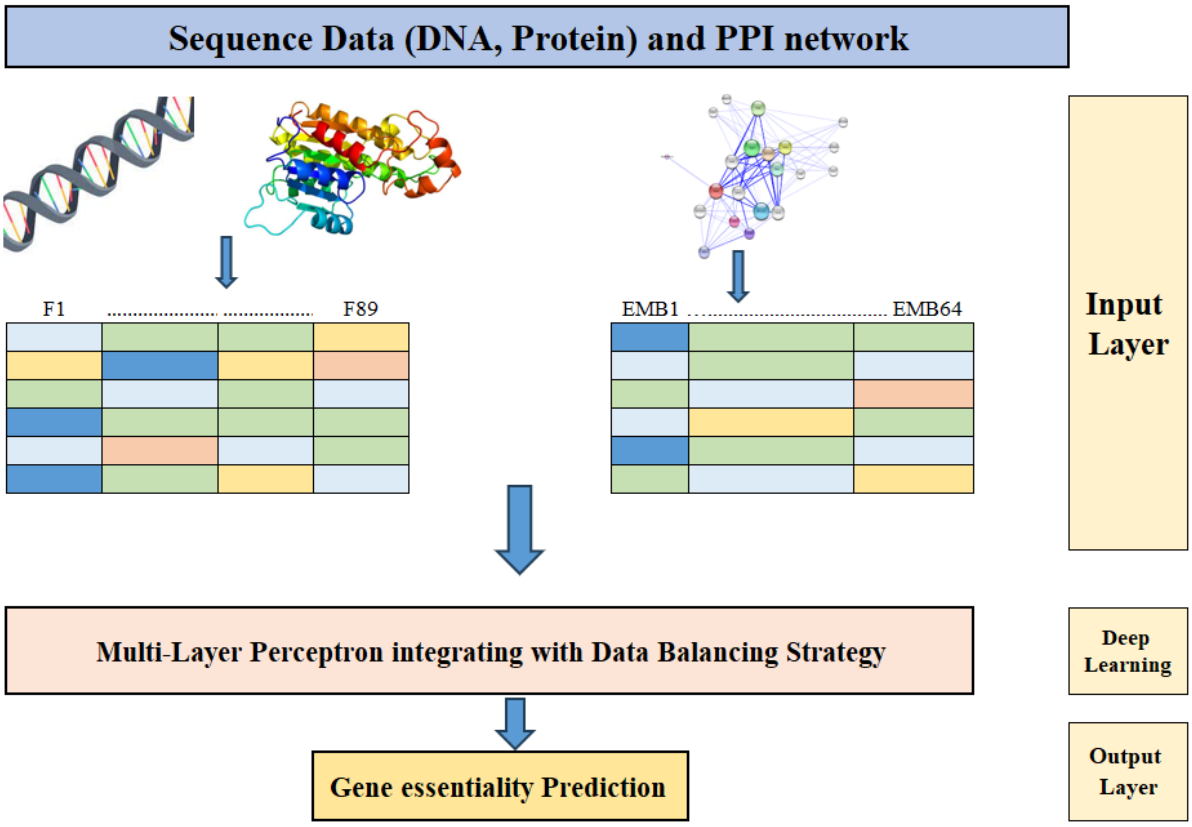


Fig. 1. Model architecture.

The dataset consists of several characteristics obtained from many kinds of biological data. There are five main elements to DNA sequence data: 64 codon frequencies, GC content, gene length, Codon Adaptation Index (CAI), and Maximal Relative Synonymous Codon Usage (RSCUmax), therefore generating 68 characteristics. With 22 characteristics, the protein sequence data consists in amino acid frequencies and protein length. Furthermore, automatically learning 64 features for every gene in the Protein-Protein Interaction (PPI) network is a network embedding technique known as Node2Vec. Comprising 153 characteristics in all, the dataset combines PPI network, DNA sequence, and protein sequence insights.

*d) A deep learning method for handling imbalanced data using MLP and ADASYN*: In classification challenges, imbalanced datasets provide a significant challenge since models often show bias towards the majority class, therefore compromising generalizing for the minority class. This work generates additional synthetic samples for the minority class by using a Multi-Layer Perceptron (MLP) model in combination with ADASYN (adaptive synthetic sampling) [2]. This approach increases classification efficiency and guarantees a fairer dataset. Data preparation, model architecture design, training with optimization strategies, and performance evaluation constitute part of the approach. The proposed model is meant to identify both non-essential and essential human genes. Along with characteristics derived from the Protein-Protein Interaction (PPI) network, feature extraction is done using DNA and protein sequences. Node2vec helps to automatically extract PPI features. Following their aggregation into a single feature vector with 153 attributes, the acquired features serve as the MLP model's input layer.

*e) Data preprocessing and class balancing*: First loaded and preprocessed is the dataset whereby the feature matrix separates from the target variable. The feature distribution is standardized using StandardScaler, therefore turning the data into zero, and its variance is one. The class imbalance in the dataset presents a major challenge that can produce biased predictions. This is treated with ADASYN. By a data-driven approach, ADASYN generates synthetic cases for the minority class unlike conventional oversampling techniques, therefore guaranteeing a more accurate distribution. Using stratified sampling to maintain class ratios, the resampled dataset is next split into training and testing sets (80% training, 20% testing).

*f) MLP model architecture*: The proposed MLP model consists of multiple layers meant to find complex trends in the data. An Input Layer of 153 neurons makes up the architecture and represents the count of retrieved features from PPI networks, protein sequences, and DNA sequences. There are 1024 hidden layers using GELU activation, 512 hidden layers using GELU activation, and 256 hidden layers using GELU activation. Batch Normalization to improve training stability and Dropout (0.03) to minimize overfitting follows each hidden layer. Given a binary classification job, a solitary neuron using Sigmoid activation. The model parameters are presented in Table I.

*g) Optimization and regularization strategies*: Several optimization techniques were used to reduce overfitting and enhance the training process: Optimizer: The model uses AdamW, an adaptive optimizer that combines weight decay to minimize strong weight changes. Learning rate scheduling is done using a Cosine Decay Learning Rate method, therefore enabling a slow drop in the learning rate throughout training periods rather than abrupt changes [3], [4]. This approach increases stability and convergence. Class Weights: The loss function is changed to give the minority class (class 0: 0.8, class 1: 1.5 more relevance to solve class imbalance.

*h) Overfitting prevention and performance enhancement*: Batch Normalization: Preserves a constant activation distribution, accelerating convergence and increasing generalizing ability, so improving the generalization of the model. Dropout (0.03): Randomly deactivates a portion during training to reduce reliance on specific neurons and hence prevent overfitting. Early Stopping: Checks validation loss and stops training should no improvement be observed after 50 epochs, therefore restoring the weight of the ideal model. Automatically lowers the learning rate by 50% once a validation loss plateaus, therefore enabling continuous improvement of model performance.

TABLE I. MODEL PARAMETERS

| Component | Details |
|---|---|
| Input Layer | Number of features in the dataset (153) |
| Hidden Layer 1 | 1024 nodes, Activation: GELU, Dropout: 0.03 |
| Hidden Layer 2 | 512 nodes, Activation: GELU, Dropout: 0.03 |
| Hidden Layer 3 | 256 nodes, Activation: GELU, Dropout: 0.03 |
| Output Layer | 1 node, Activation: Sigmoid |
| Epochs | 100 |
| Early Stopping | Patience:25 epochs |
| Optimizer | AdamW with Cosine Decay Learning Rate |

## V. IMPLEMENTATION DETAILS

Using Python 3.8, TensorFlow and Keras for deep learning, and Scikit-learn for data preparation and evaluation, the proposed model was run. StandardScaler helped us standardize the data such that every feature fits a zero-mean, unit-variance distribution. ADASYN was used to generate synthetic samples for the minority class before stratified sampling split the dataset into 80% training and 20% testing, therefore helping to reduce class imbalance. Using GELU activation, the MLP model consisted of three hidden layers with 1024, 512, and 256 neurons correspondingly, succeeded by Batch Normalization and Dropout (0.03) to increase generalization and reduce overfitting. AdamW, combined with Cosine Decay Learning Rate Scheduling, helped to improve the model, guaranteeing training stability. Using Early Stopping (patience = 25) to prevent overfitting, the model ran through 100 epochs. Although the Quadro P620 helps CUDA acceleration, its computational capacity is less than that of high-end GPUs such the Tesla V100, which causes extended training times even if the experiments were conducted on a system with an Intel Core

i7-10750H CPU (2.60 GHz), 8GB RAM, and an NVIDIA Quadro P620. Still, careful change of batch size and learning rate helped to preserve training efficiency. The performance of the model in important gene categorization was shown by accuracy, sensitivity, specificity, and AUC-PR evaluation.

## VI. Implementation and Results

*a) Data collection*: The Essential Genes Data (DEG) collection consists of twenty freely available sets of basic human genes [23]. To ensure complete coverage of important genes, we obtained and included all 20 data sets in our study [18-20], [24-26], [27-29] . We categorized essential genes found in a minimum of five independent datasets if around 10% of human genes are essential [20]. This criterion led us to identify 2162 essential genes, nearly 10% of the human genome. The genes not categorized as essential in the DEG database were labeled as non-essential. Table II presents Datasets Database. Protein-Protein Interaction (PPI) Network Data included only physically proven interactions among human proteins, derived from experiments. Eliminating self-interactions and many small, disconnected subgraphs helped to improve the dataset to produce a PPI network with 17,786 nodes and 355,646 edges. Embedding features reflecting the connectivity patterns of every gene within the network were obtained from this well-chosen interaction network. From the PPI network, each gene derived 64 embedding features overall. Essential genes: 2145; genes with both sequence features and network embedding. Non-essential genes: 7,680. There are 9,825 examples in the last dataset, and each one features 153 attributes.

*b) Evaluation metrics*: The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) evaluates the model's performance in fit for balanced classification situations when all classes have roughly equal instance counts. When there is uneven classification, the Precision-Recall (PR) curve provides a more perceptive evaluation. The Area Under the Precision-Recall Curve (AP) is a more representative measure than the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) since human essential gene prediction represents an unbalanced classification problem. We incorporate many statistical performance measures in addition to AUC and AP, namely Sensitivity, Specificity, Positive Predictive Value, and Accuracy, defined in Eq.(1) to (4).

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (1)$$

$$\text{Specificity} = \frac{TN}{FP+TN} \quad (2)$$

$$\text{Positive Predictive Value} = \frac{TP}{TP+FP} \quad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \quad (4)$$

where, TP (True Positives): The number of correctly classified essential genes.TN (True Negatives): The number of correctly classified non-essential genes. FP (False Positives): The number of non-essential genes misclassified as essential. FN (False Negatives): The number of essential genes misclassified as non-essential. Especially in addressing the class imbalance inherent in essential gene prediction, these measures provide a complete evaluation of the classification performance of the model.

*c) Ablation study*: In this section, an ablation study was conducted to assess the impact of various components of the Multi-Layer Perceptron (MLP) model on the classification accuracy of essential genes. The primary objective was to identify the most influential factors within the model and evaluate how the exclusion or modification of specific parameters or inputs influences overall model performance.

To ensure the optimality of the selected model architecture (1024-512-256) and dropout rate (0.03), a series of controlled experiments were performed. The purpose of these experiments was to examine the effect of these variables on model performance, confirming that each design choice contributed positively to enhancing accuracy while also addressing challenges such as overfitting and class imbalance.

TABLE II. Datasets Database

| Data | Database | File name |
|---|---|---|
| DNA and protein sequence data | Ensembl [30] | release 97, July 2019 |
| PPI data | BioGRID [31] | release 3.5.181, February 2020 |
| Essential genes data | DEG | Homo sapiens( DEG2006: DEG2032) |

As shown in Table III and Fig. 2 presents the results of the ablation study, comparing the performance of various MLP architectures based on several evaluation metrics. The analysis includes accuracy, stability, tendencies toward overfitting, and the model's handling of class imbalance across the selected MLP architectures.

- 1024-512-256 Architecture: This architecture provides an effective balance between training and validation accuracy, showing a significant improvement in both test accuracy and Area Under the Curve (AUC).
- 512-256-128 Architecture: While this architecture yields good test accuracy, it is lower than that of the larger architecture. However, it achieves the best test loss among the configurations tested.
- 2048-1024-512 Architecture: This model achieves the highest training accuracy but is prone to overfitting. Nevertheless, it performs well on the validation data.

Table IV outlines the performance metrics for models with varying dropout rates, illustrating how train accuracy, validation accuracy, test accuracy, AUC scores, and loss are influenced by different dropout values:

- Dropout = 0.0 (No Dropout): In this configuration, overfitting is observed, as the model excels on the training data but struggles to generalize to validation and test data.
- Dropout = 0.03: This rate strikes an optimal balance between regularization and model performance. It reduces overfitting while maintaining high accuracy and AUC scores, yielding the best test accuracy (~94%) and the lowest test loss (~0.20).

- Dropout = 0.1: This configuration results in under fitting due to excessive regularization. It produces the lowest accuracy on the test data and the lowest AUC scores, although it achieves the lowest test loss (~0.19), suggesting some improvement in generalization.

In conclusion, a dropout rate of 0.03 provides the best trade-off between mitigating, overfitting and achieving high accuracy across training, validation, and test datasets

*d)* Performance evaluation

- Comparison of Traditional Machine Learning and Deep Learning Models in Classification

As shown in Fig. 4 and Table V, Deep Learning Models vs Conventional Machine Learning. Artificial intelligence applications depend on the proper model for classification tasks since model performance varies depending on data characteristics and class equilibrium. This paper evaluated and compared the performance of standard machine learning techniques, including AdaBoost, SVM, Random Forest, and Naïve Bayes with that of a Multi-Layer Perceptron (MLP) network coupled with ADASYN, a deep learning approach. Founded on fundamental performance measures— Sensitivity, Specificity, Positive Predictive Value, and Accuracy—the assessment sought to find the most effective model for the given dataset.

Conventional models showed significant performance variability; the Support Vector Machine (SVM) proved to be rather robust in identifying positive samples with a maximum sensitivity of 0.9693. With its best overall accuracy of 0.9015, it is a well-balanced choice between sensitivity and specificity. Random Forest showed a high sensitivity of 0.9776 yet a reduced specificity of 0.7585, therefore suggesting a higher false positive rate. AdaBoost achieved an overall accuracy of 0.8428 and showed a better-balanced performance than SVM in general efficacy, although it did not surpass SVM. Naïve Bayes had the lowest sensitivity of 0.6176, indicating poor identification of positive instances, and the highest specificity of 0.8932, therefore demonstrating its effectiveness in lowering false positives. Still, its general performance in categorization was worse than that of other models.

- Main Observation

The MLP running ADASYN exceeded all conventional models with the best accuracy of 94.38%. With a sensitivity of 96.93% and an accuracy of 90.15%, the Support Vector Machine (SVM) exceeded other traditional machine learning models. With high sensitivity (97.76%) but poor specificity (75.85%), the Random Forest model suggested a higher false positive rate. Naïve Bayes showed the lowest sensitivity (61.76%) but the highest specificity (89.32%) showing better performance in reducing false positives and less efficacy in discovering positive situations. AdaBoost showed a reasonable performance; however, it fell short of SVM or deep learning. Deep learning, especially when combined with data augmentation techniques such as ADASYN, clearly improves classification performance, so it is the most effective solution for this problem. With a sensitivity of 0.9827, an overall accuracy of 0.9438, and a specificity of 0.9643, the Multi-Layer Perceptron (MLP) with ADASYN model outperformed all other methods. These findings highlight its remarkable ability for exact data classification, particularly in view of imbalance-handling techniques like ADASYN. The deep learning model produced quite improved classification results by remarkably identifying complex patterns in the sample.

TABLE III. MLP ARCHITECTURES BASED ON SEVERAL EVALUATION METRICS

| Architecture | Best Training Accuracy | Best Validation Accuracy | Test Accuracy | Best AUC | Test Loss | Number of Epochs |
|---|---|---|---|---|---|---|
| 512-256-128 | High, but lower than other architectures | Good, but lower than larger architectures | ~ 91% | ~ 0.97 | Highest among the three | 100 |
| 1024-512-256 | Very high, with better stability | Very good with reduced fluctuations | ~ 93% | ~ 0.98 | Relatively lower | 100 |
| 2048-1024-512 | Highest, but with overfitting | Very good performance with slight fluctuations | ~ 92% | ~ 0.98 | Lower than the smaller architecture, but not much improved | 100 |

TABLE IV. PERFORMANCE METRICS FOR MODEL WITH VARYING DROPOUT RATES

| Dropout | Train Accuracy | Validation Accuracy | Test Accuracy | Train AUC | Validation AUC | Test AUC | Train Loss | Validation Loss | Test Loss |
|---|---|---|---|---|---|---|---|---|---|
| 0 | ~99% | ~95% | ~93% | ~1.00 | ~0.98 | ~0.97 | Low | Higher | ~0.22 |
| 0.03 | ~98% | ~96% | ~94% | ~0.99 | ~0.98 | ~0.975 | Moderate | Lower | ~0.20 |
| 0.1 | ~97% | ~94% | ~92% | ~0.98 | ~0.97 | ~0.965 | Higher | Lower | ~0.19 |

- Evaluation of Model Performance During Training and Testing

The training process was assessed over numerous epochs using accuracy, AUC, and loss measures as shown in Fig 5. During the first epoch, the training accuracy and AUC showed a rapid rise and then stabilized at about 1.0, indicating that the model efficiently absorbed the training data. With a final test accuracy exceeding 0.9 and a test AUC over 0.98, the validation accuracy and AUC show consistent enhancement, approaching the test performance, demonstrating strong classification skill. Whereas the validation loss showed volatility before steadying, the loss curves show that the

training loss fell sharply in the first epoch and stayed low. The test loss stayed constant, suggesting that the model fits fresh data rather well. These results support the durability and efficiency of the model in separating non-essential from essential genes.

TABLE V. PERFORMANCE COMPARISON OF MLP WITH ADASYN, ADABOOST, SVM, RANDOM FOREST, AND NAÏVE BAYES

| Model | Sensitivity | Specificity | Positive Predictive Value | Accuracy |
|---|---|---|---|---|
| AdaBoost | 0.8495 | 0.8359 | 0.8403 | 0.8428 |
| Support Vector Machine (SVM) | **0.9693** | 0.8327 | 0.8548 | **0.9015** |
| Random Forest | 0.9776 | 0.7585 | 0.8044 | 0.8689 |
| Naïve Bayes | 0.6176 | **0.8932** | 0.8546 | 0.7543 |
| MLP + ADASYN (Deep Learning) | **0.9827** | **0.9043** | **0.9126** | **0.9438** |

- Analysis of Training and Evaluation Curves
  - Fig. 3 presents the loss and accuracy curves during the training and evaluation phases across five folds using K-Fold Cross Validation.
  - The loss curve shows a rapid decrease in loss values during the early stages of training, reflecting the model's quick adaptation to the data. However, some fluctuations in the evaluation loss values are observed, which might indicate potential for slight overfitting.
  - The accuracy curve in Fig. 6 demonstrates that the model achieves a high accuracy rate exceeding 90% after a few training epochs, with the performance stabilizing afterward. The small gap between the training and evaluation curves suggests the model's stability and minimal overfitting.

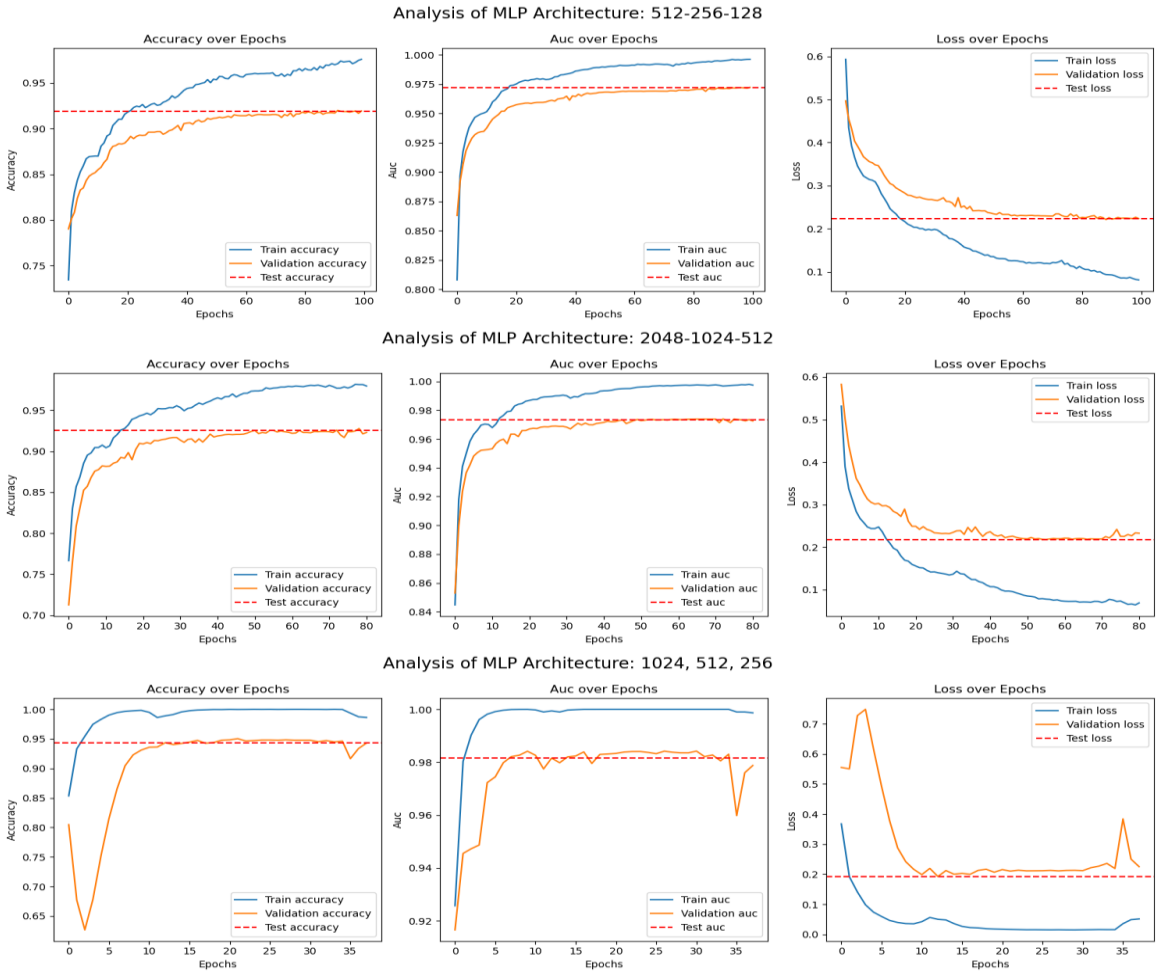


Fig. 2. Analysis of MLP architectures.

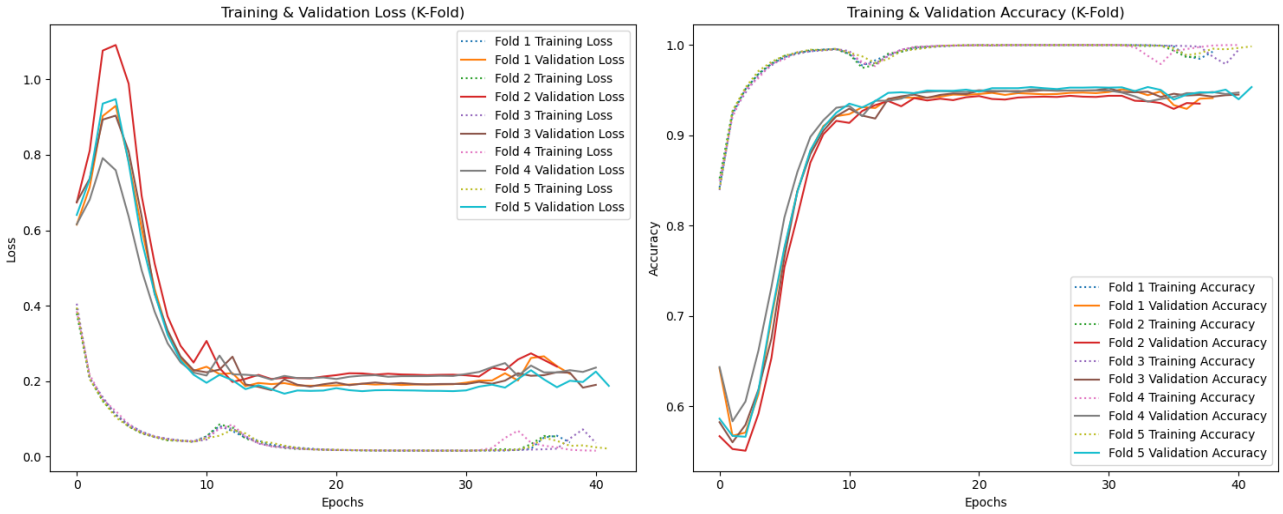


Fig. 3. Loss and accuracy curves.

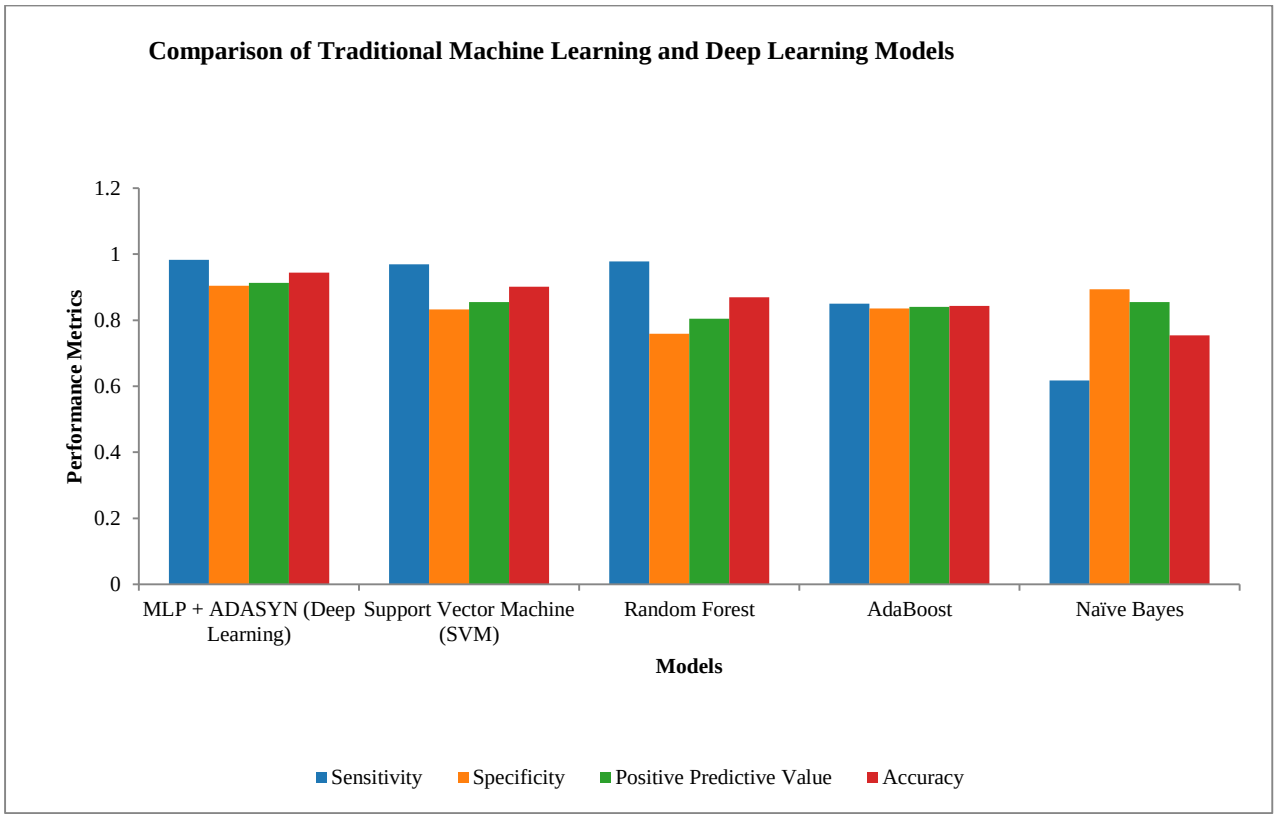


Fig. 4. Performance comparison of MLP with ADASYN, AdaBoost, SVM, random forest, and naïve bayes.

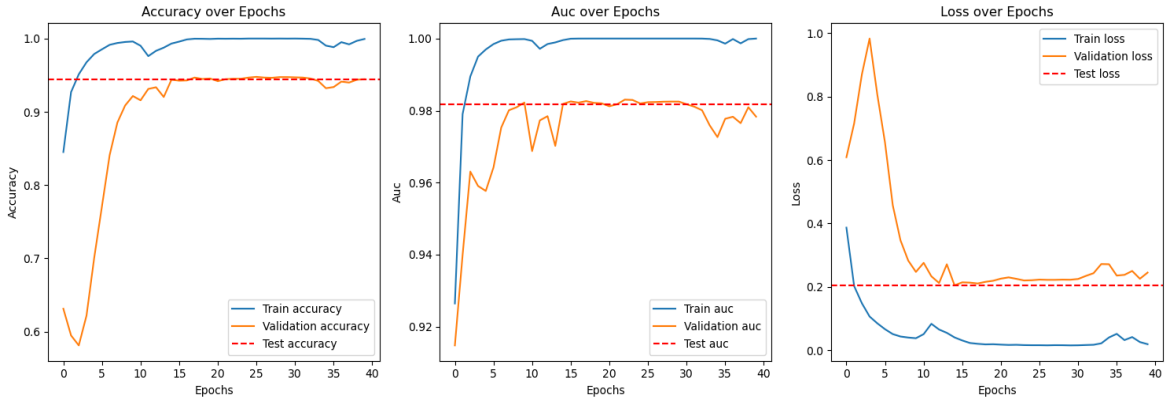


Fig. 5. Training and evaluation metrics over epoch.

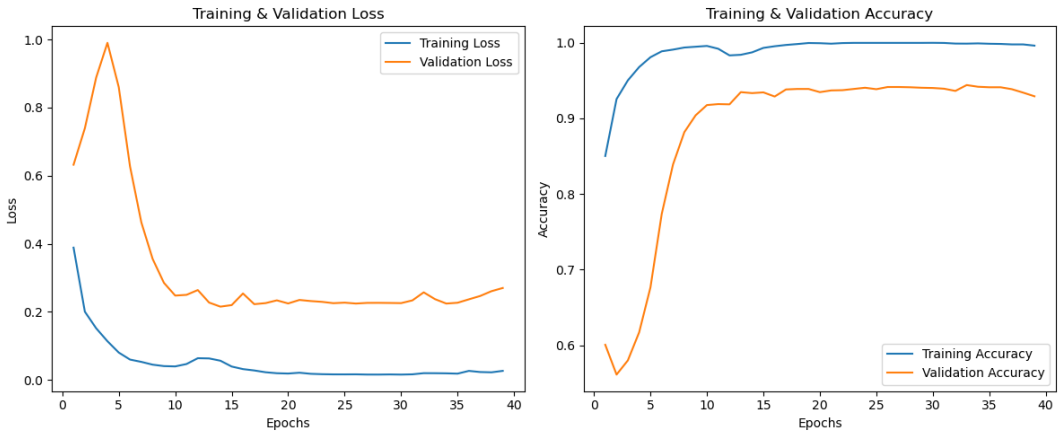


Fig. 6. Training and validation.

- Receiver Operating Characteristic (ROC) Curve and the Precision-Recall (PR) Curve

In Fig. 7, the ROC curve reflects the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR). The results show an AUC value of 0.98, indicating the model's high ability to discriminate between different classes.

The Precision-Recall curve illustrates the relationship between precision and recall, achieving a PR AUC value of 0.98. This indicates the model's effectiveness in maintaining a high balance between precision and recall, which is crucial in scenarios with imbalanced datasets.

The training and evaluation curves show a gradual improvement in model performance, while the high AUC values in both the ROC and Precision-Recall curves highlight the model's strong classification capability.

The model demonstrates high efficiency in classifying data, achieving high accuracy and excellent AUC values, which reflects its ability to effectively separate the target classes.

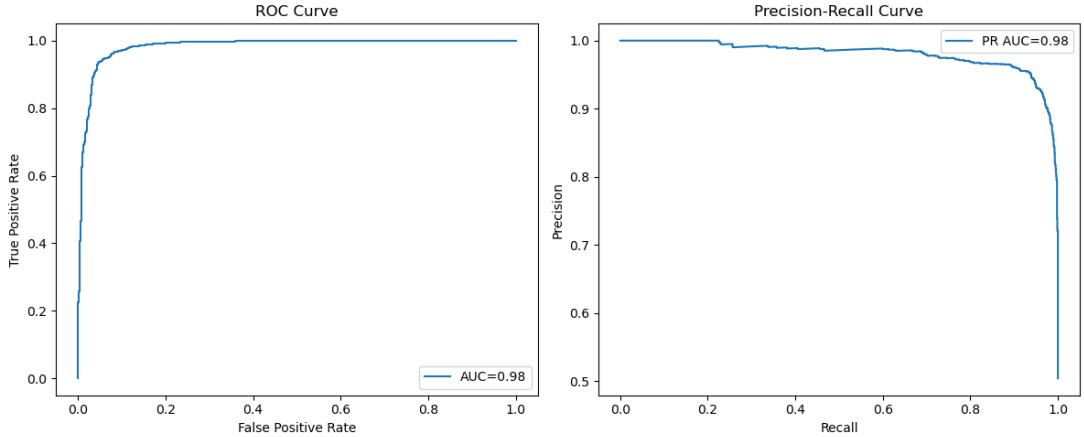


Fig. 7. Model Performance evaluation: ROC and precision-recall curves.

## VII. CONCLUSION

*a) Conclusion*: By combining numerous biological data sources DNA sequence features, protein sequence attributes, and protein-protein interaction (PPI) this work developed a deep learning system for anticipating important human genes. With 94.38% accuracy, 98.27% sensitivity, and 90.43% specificity, the proposed MLP model using ADASYN showed improved performance relative to standard machine learning models. Especially in the management of imbalanced datasets and autonomously recognizing complex patterns in large-scale biological data, the results highlight the advantages of deep learning approaches in important gene prediction. This model is a potential tool for biological study since the combination of sequence-based properties and network topology produced a more complete and accurate classification of significant genes. Additionally, improving model generalization and stability were regularization techniques like Batch Normalization, Dropout, and Learning Rate Scheduling. The study underlined the need to balance class distribution and showed how much ADASYN enhanced model performance in predicting important genes in the minority class.

*b) Future directions*: Notwithstanding the positive results, there are still several paths for further improvement and research: Enhancing Feature Representation, combining epigenetic modifications, gene expression patterns, and functional annotations could increase the predictive power of the model. Examining graph-based embeddings outside Node2Vec including Graph Neural Networks (GNNs) may improve the representation of protein-protein interaction (PPI) networks. Application in Disease Gene Forecasting, since many important genes are linked to diseases, using this model to predict disease-related genes could have significant effects on pharmaceutical research and tailored therapy. For important gene prediction, the proposed deep learning system presents a strong, scalable, and well-performing approach. This work combines class-balancing methods, deep learning, and biological data to improve the biological relevance and accuracy of gene-categorizing algorithms.

## DATA AVAILABILITY

All data used in this study are freely accessible from public databases:

Protein-protein interaction data are available from BioGRID database at http://thebiogrid.org/download.php.

Essential genes data and the corresponding sequence data from DEG database are available at

http://tubic.tju.edu.cn/deg/

DNA sequence and protein sequence data are available at https://useast.ensembl.org/Homo_sapiens/Info/Annotation

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# Personalized Recommendation for Online News Based on UBCF and IBCF Algorithms

Wei Shi[1]*, Yitian Zhang[2]
School of Humanities and Law, Nanchang HangKong University, Nanchang 330063, China[1]
The Centre for Translation and Intercultural Studies, The University of Manchester, Manchester, M139PL, UK[2]

***Abstract*—With the popularization of the Internet and the widespread use of mobile devices, online news has become one of the main ways for people to obtain information and understand the world. However, the increasing number and variety of news often cause users to feel troubled when searching for content of interest. To solve this problem, the first step is to design a personalized recommendation model for online news. Based on this model, a new personalized recommendation model is designed by combining the item-based collaborative filtering (IBCF) and the user-based collaborative filtering (UBCF). The experimental results showed that the average scores of the volunteers for the performance indicators, coverage indicators, and satisfaction indicators of the model were 85 and 93, 86, respectively. This system has high accuracy, low resource consumption, and higher user satisfaction, providing a new algorithmic approach for the field of recommendation models. The contribution of research is not only improving the accuracy of recommendations, but also increasing the diversity of recommendations, effectively solving the problem of data sparsity and real-time news. By introducing a tag propagation network for clustering analysis of users and projects, the recommendation results are further optimized and user satisfaction is improved. In addition, the research also realizes efficient data processing and storage through real-time user data collection and distributed data processing technology, which significantly improves the performance and response speed of the system.**

***Keywords*—IBCF algorithm; UBCF; collaborative filtering; news recommendations; label promotion network**

## I. Introduction

With the rapid development of the Internet, online news has become an important way for people to obtain information. However, faced with massive news information, how to effectively filter out content that users are interested in and improve their reading experience has become an urgent problem to be solved. Personalized recommendation systems have emerged, which analyze the interests, preferences, and behavioral habits of users to recommend relevant news content, thereby improving user satisfaction and loyalty [1-2]. Collaborative filtering algorithm is an important method in personalized recommendation systems, mainly divided into user-based collaborative filtering (UBCF) and items-based collaborative filtering (IBCF). However, single UBCF or IBCF algorithms have certain problems in the recommendation process [3]. For example, the UBCF algorithm, in news platforms with a large user base and diverse preferences, may be less accurate due to the addition of new users, due to the lack of understanding of the interests of new users. On the other hand, IBCF may not be able to effectively recommend diverse content when users have a low interest in specific news topics, because it mainly relies on the similarity between news projects and ignores the personalized needs of users. In view of the above issues, the study first designs a network news recommendation index model based on the characteristics of network news recommendation. In response to the inherent shortcomings of UBCF and IBCF algorithms, the two are innovatively combined. The Label Promotion network is used to perform clustering analysis on users and projects. By utilizing known user behavior information and news attribute information, the data sparsity is solved. The research question focuses on how to combine item-based collaborative filtering (IBCF) and user-based collaborative filtering (UBCF) algorithms to improve the accuracy and diversity of recommendations. The purpose of the research is to integrate IBCF and UBCF algorithms and introduce the label promotion network for cluster analysis, optimize the recommendation results, improve user satisfaction, and provide an efficient algorithm method for the personalized recommendation field of online news. The paper mainly has four parts. The first part is the research status of recommendation models. The second part combines the IBCF algorithm and UBCF algorithm to design a new IBCF-UBCF network news personalized recommendation model. The third part conducts comparative experiments on the algorithm performance. The fourth part summarizes the research content.

The innovation of this method is mainly reflected in the following aspects: Firstly, by integrating effectiveness, coverage, and user satisfaction, a comprehensive and scientific online news personalized recommendation index model has been constructed, providing an effective evaluation system for the continuous improvement of recommendation systems. Secondly, this study adopts streaming distributed data collection technology for real-time user data collection, and combines the Apache Spark framework with the ZooKeeper cluster to achieve efficient data processing and storage, effectively solving the bottleneck problem of data processing and storage. In addition, this method innovatively combines the UBCF algorithm based on user social relationship strength and interest similarity with the IBCF algorithm based on attribute similarity, improving the accuracy and diversity of recommendations. Finally, by categorizing data streams and establishing indexes, the pertinence of data processing and retrieval efficiency have been further improved. These innovative points collectively enhance the interactivity and personalization of news recommendations, providing users with higher quality services.

The main contribution of this study is to propose a novel online news personalized recommendation model that combines item-based collaborative filtering (IBCF) and user-based collaborative filtering (UBCF). By integrating these two collaborative filtering algorithms, this study not only improves the accuracy of recommendations, but also increases the diversity of recommendations, effectively solving the problems of data sparsity and real-time news. In addition, by introducing label promotion networks for clustering analysis of users and items, the recommendation results were further optimized and user satisfaction was improved. This study not only provides new algorithmic methods for personalized recommendation systems, but also provides strong technical support for the development of the online news industry.

## II. Related Works

With the continuous development of the economy and society, more researchers are paying attention to injecting more intelligent elements into personalized services. Mizgajski et al. proposed a emotional perceived recommendation system method to address the effectiveness of emotional factors in recommendation systems. The emotional response of user self-evaluation was used to recommend news. The results showed that incorporating pleasant emotions into collaborative filtering recommendations had the best performance. It had further research value in selecting emotional response recommendations [4]. Goyani et al. combined two methods to improve recommendation performance to address the limitations of collaborative filtering and content filtering in movie recommendation systems. To solve the user similarity calculation, experimental results showed that this method could improve the accuracy. In addition, this paper also reviewed the different technological applications of recommendation systems to promote research progress in this field [5]. To explore the user preferences for specific news, Symeonidis et al. combined the intra session and inter session item transfer probabilities of users, revealing both short-term and long-term intentions. Experimental evaluation showed that this method could better capture the similarity between items jointly selected by users within and between consecutive sessions. It was superior to state-of-the-art algorithms [6]. Tewari et al. proposed a recommendation method based on a semi-automatic encoder, which integrated user ratings and other additional information to address the information overload and user interest matching in recommendation systems. This method had improved accuracy, recall, and F-value evaluation indicators compared to other popular methods. The top 10 recommendation results were more accurate [7]. Wang et al. aimed to address the large data volume, cold start, and data sparsity in modern commercial website recommendation systems by transforming large data volume into a large user group. The k-means clustering was applied to partition user groups. Then it was combined with collaborative filtering and content-based recommendation algorithms. When the accuracy and recall were about 0.4 and 0.8, the F value was the highest [8].

Gao, H et al. investigated the implicit knowledge in Industrial Internet of Things (IIoT) using collaborative learning techniques to address the difficulty in selecting suitable APIs. A recommendation method for enhancing matrix factorization models was proposed. This method was effective and superior in both real datasets and industrial system scenarios [9]. Zhu et al. proposed a news recommendation method based on deep attention neural network (DAN) to address the existing recommendation methods being unable to handle the dynamic diversity of news and user interests. This method used parallel convolutional neural networks (CNN) and recurrent neural networks (RNN) to aggregate user interest features and capture hidden order features of user clicks. The results showed that this method had superiority and effectiveness, with an accuracy rate of 95.5% in comparative experiments [10]. Huang et al. proposed an spatiotemporal long short-term memory network based on attention mechanism (ATST-LSTM) method to address the lack of spatiotemporal contextual information in Point of Interest (POI) recommendation. The results showed that it outperformed other recommendation methods [11]. Li and others proposed a new method for jointly processing new users and long tail recommendations in recommendation systems. By learning auxiliary information such as user attributes and social relationships, the cold start for new users is solved. Experimental results showed that this method outperformed existing best methods in social recommendation on real datasets such as images, blogs, videos, and music [12]. Zhao et al. proposed a NeuNext framework to address the complex sequence patterns and rich context in sparse user check-in data. Joint learning utilized POI context prediction to assist in the next one. Experimental results showed that this method outperformed other recommendation methods [13], as shown in Table I.

Although the above methods have made significant progress in personalized recommendation systems, there are still some shortcomings. In the previous study, most personalized recommendation systems face the problems of sparse data, cold start and insufficient diversity of recommendations. For example, the emotive perception recommendation system proposed by Mizgajski et al. fails to fully consider the dynamic changes of users' interests, resulting in the inability to match the recommended content with users' real-time needs. Goyani et al.'s work, while combining collaborative filtering and content filtering, still faces the challenge of reduced accuracy in sparse data. Symeonidis et al.'s research focused on capturing short - and long-term user intentions, but failed to effectively address the long tail recommendation problem. This paper proposes a method to combine UBCF and IBCF to better capture the interest of new users and solve the cold start problem by introducing social relationships between users, while IBCF can improve the diversity of recommended content and avoid the uniformity of recommendation results by focusing on project attributes. At the same time, the research also adopts the flow distributed data collection technology to ensure the acquisition of real-time user data, and further enhance the response ability of the system in the dynamic environment. Through the above advantages, the research can effectively overcome the shortcomings in the previous work and provide an efficient personalized recommendation solution for online news. This method not only better meets the growing individual needs of users, but also provides new ideas for research and application in related fields.

TABLE I A REVIEW OF RELATED STUDIES

| Researchers | Proposed Method | Experimental Results |
|---|---|---|
| Mizgajski et al. [4] | Emotion-aware recommendation system method | Best performance by integrating pleasant emotions into collaborative filtering recommendations |
| Goyani et al. [5] | Combining two methods to improve recommendation performance | Improved accuracy of recommendations |
| Symeonidis et al. [6] | Combining user's intra-session and inter-session item transition probabilities | Better capture of item similarities commonly chosen by users within and across consecutive sessions |
| Tewari et al. [7] | Recommendation method based on semi-automatic encoders | improved accuracy, recall, and F-measure evaluation metrics |
| Wang et al. [8] | Converting big data into a large user group, combining collaborative filtering and content-based recommendation algorithms | Highest F-measure when precision and recall are approximately 0.4 and 0.8 respectively |
| Gao et al. [9] | Enhancing matrix factorization models using collaborative learning techniques | Effective and superior performance in real datasets and industrial system scenarios |
| Zhu et al. [10] | A news recommendation method based on deep attention neural networks | Superior and effective achieving 95.5%accuracy in comparative experiments |
| Huang et al. [11] | An attention-based spatio-temporal long short-term memory network approach | Superior to other recommendation methods |
| Li et al. [12] | A new method for jointly handling new users and long-tail recommendations | Superior performance compared to the best available methods in social recommendations on real datasets (eg, images, blogs videos, and music] |
| Zhao et al. [13] | NeuNext framework | Superior to other recommendation methods |

## III. A PERSONALIZED RECOMMENDATION MODEL FOR ONLINE NEWS BASED ON COLLABORATIVE FILTERING

This chapter is mainly divided into two sections. The first section first designs a personalized recommendation index system for online news. Based on this, a network news recommendation model based on the IBCF is designed. The second section mainly combines the IBCF with the UBCF. A series of improvements are made to the two algorithms, and an IBCF-UBCF network news recommendation model is designed.

### A. Personalized Recommendation Index System and Algorithm Design for Online News

The personalized recommendation index model for online news is an important tool for measuring the performance of recommendation systems, mainly composed of three aspects. Firstly, there are performance indicators, including accuracy, recall, F1 value, and AUC value. These indicators can effectively measure the accuracy and reliability of recommendation algorithms, ensuring that users receive high-quality news recommendations [14-15]. Secondly, there are coverage indicators that cover popular content, long tail content, diversity, and personalization. These indicators aim to evaluate the coverage ability of recommendation systems for various types of news, to meet the diverse interests and needs of users [16-17]. Finally, there are user satisfaction indicators, including timeliness, user retention rate, user rating, and user feedback. These indicators can reflect the satisfaction and acceptance of users towards recommendation results. It is an important basis for optimizing recommendation systems. In summary, the personalized recommendation index model for online news integrates three aspects: effectiveness, coverage, and user satisfaction, providing a comprehensive and scientific evaluation system for the continuous improvement of recommendation systems [18-19]. The personalized recommendation index model for online news is shown in Fig. 1.

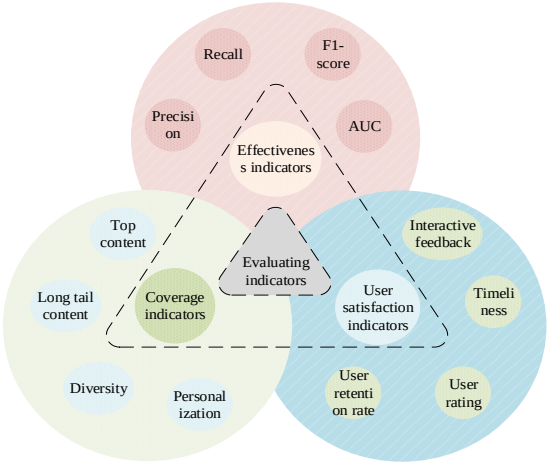



Fig. 1. A personalized recommendation index model for online news.

Based on the personalized recommendation index model for online news, the study first uses the IBCF algorithm to calculate the similarity between news, which is the core of the algorithm. The general IBCF algorithm uses chord similarity, as shown in Eq. (1).

$$sim(i,j) = \frac{i * j}{\| i \|_2 * \| j \|_2} \quad (1)$$

In Eq. (1), $i$ represents a vector in the user space. $j$ represents another vector in user space. However, cosine similarity assumes that the relationship between features is linear. For news data with non-linear relationships, it may not be the best choice. The adjusted cosine similarity takes this into account. Therefore, the mathematical expression for the

modified cosine similarity is shown in Eq. (2).

$$sim(i,j)=\frac{\sum_{u\in U_{ij}}(r_{u,i}-\bar{r}_1)*(r_{u,j}-\bar{r}_j)}{\sqrt{\sum_{u_i}(r_{u,i}-\bar{r}_i)^2}*\sqrt{\sum_{u_j}(r_{u,j}-\bar{r}_j)^2}} \quad (2)$$

In Eq. (2), $r_{u,j}$ stands for the rating of $u$ user on $i$. $\bar{r}_i$ represents the mean of the project $i$ rating vector. $\bar{r}_j$ represents the mean of the project $j$ rating vector. Fig. 2 displays the IBCF.

In Fig. 2, it is assumed that similar users A, B, and C exist, and items a, b, c, and d represent different news types. Each user's interest in a particular project forms an interaction matrix. User A's preference for item a, user B's preference for item b and item c, and user C's preference for item a form the core basis of the recommendation system. The reason why the study divided users A, B, and C into three categories lies in their similarities in interests and behaviors. User similarity is calculated by assessing their ratings or preferences for shared items. Specifically, user A likes item a, which belongs to a particular interest category, possibly news about a particular topic. User B is interested in both project b and Project c, reflecting A preference for similar topics, but may be somewhat different from user A's interest. User C: Liking item a may indicate significant differences with user B's interests and similarities with user A's interests. Through the above analysis, users' behavior in social networks or news apps can characterize their interests. In news recommendation, data sparsity is mainly reflected in the interaction matrix between users and news. This matrix is usually very large because it contains all user ratings or preference information for all news. However, in practical situations, users often only browse or evaluate a small portion of news, which results in most elements in the matrix being zero, forming a high-dimensional and sparse matrix. To address this issue, the study uses Singular Value Decomposition (SVD) for prediction filling, transforming the original high-dimensional sparse matrix into a low dimensional dense matrix. This can to some extent reduce the data sparsity. The algorithm flow is shown in Fig. 3.

Data preprocessing collects user-news interaction data, forms a rating matrix, and fills missing values (unobserved user news-interactions) with 0 or other appropriate default values. SVD is calculated. The SVD function in the linear algebra library is used to decompose the scoring matrix R, resulting in three matrices: $U$, $\sum$, and $V\wedge T$. SVD is truncated. According to the requirements, the first $k$ largest singular values are selected to be retained, while the remaining smaller singular values are ignored. The $U$, $\sum$, and $V\wedge T$ matrices are updated to include the first singular value. The user hidden vector is calculated. For each user, its corresponding left singular vector is divided by the square root of the corresponding singular value to obtain the user hidden vector. The news hidden vector is calculated. For each news, its corresponding right singular vector is divided by the square root of the corresponding singular value to obtain the news hidden vector. User-news rating is predicted. For a given user and news, the predicted rating between them is calculated. Missing values are filled in. The missing values (i.e. elements with 0) in the original scoring matrix are replaced with predicted scores. For evaluation and optimization, the dataset is divided into training and testing sets. The parameter $k$ and possible regularization parameters are adjusted to optimize the performance of the model. Assuming there is a user news interaction matrix $R$ for $m\times n$ ($m$ represents the number of users and $n$ represents the number of news), SVD can decompose $R$ into three matrices multiplied by each other, as shown in Eq. (3).

$$R=U\sum V\wedge T \quad (3)$$

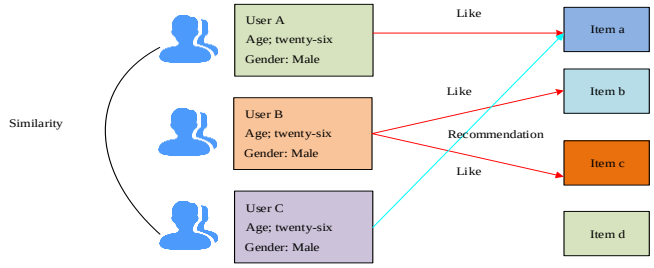



Fig. 2. Schematic diagram of IBCF algorithm.

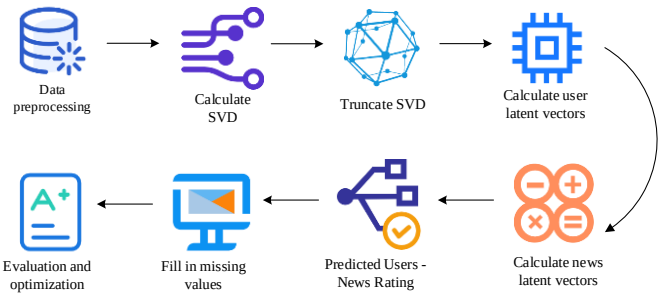



Fig. 3. The basic process of data filling based on clustering filling method.

In Eq. (3), $U$ represents a unitary matrix of $m \times n$. Its column vector is the left singular vector of $R$. $\sum$ is a diagonal matrix of $k \times k$, with its non-zero elements (i.e. singular values) arranged in decreasing order. $V \wedge T$ is a unitary matrix of $k \times n$, and its column vector is the right singular vector of $R$. To reduce computational complexity and solve the data sparsity, the first $k$ largest singular values are retained and the remaining smaller singular values are ignored. The purpose of SVD is to reduce computational complexity and solve data sparsity problems by preserving the first $k$ largest singular values. Keeping these largest singular values ensures that we still capture most of the important information, while reducing unnecessary calculations by ignoring smaller singular values. Thus, while the dimensions of $U$ and $V \wedge T$ are related to the number of users and news, respectively, the dimension of $\sum$ is determined by the number of retained singular values k. This method effectively realizes the reduction and approximation and solves the problem of data sparsity. The approximate expression of the original $R$ matrix is displayed in Eq. (4).

$$R \approx U\_k \sum\_k V \wedge T\_k \tag{4}$$

In Eq. (4), $U\_k$ is the matrix composed of the first $k$ columns of $U$. $\sum\_k$ is a matrix composed of the first $k$ columns and first $k$ rows of $\sum$. $V \wedge T\_k$ is a matrix composed of the first $k$ columns of $V \wedge T$. This process is called Truncated SVD. Then, $U\_k$ and $V \wedge T\_k$ can be used for prediction filling. Unobserved user news interaction values can be estimated based on existing user behavior data and news content information, as shown in Eq. (5).

$$r\_\{ui\} \approx p\_u \wedge T q\_i \tag{5}$$

In Eq. (5), $p\_u$ is the hidden vector of user $u$. $q\_i$ is the hidden vector of news $i$. The $p\_u$ is shown in Eq. (6).

$$p\_u = \frac{U\_k[:,u]}{sqrt(\sigma^2)} \tag{6}$$

In Eq. (6), $\sigma$ is the $k$-th singular value. The $q\_i$ is shown in Eq. (7).

$$q\_i = \frac{V\_k[:,i]}{sqrt(\sigma^2)} \tag{7}$$

### B. Design and Improvement of UBCF-IBCF

The IBCF algorithm has certain advantages in news recommendation, such as capturing the similarity between news and alleviating the cold start problem for new users and news. However, it also has some shortcomings. Although research has solved the data sparsity through SVD, news usually has timeliness and real-time, with a large number of news updates every day [20-21]. Therefore, it is necessary to frequently calculate the similarity matrix between news, which will increase the computational burden of the system. For uncommon news, due to the lack of sufficient interaction data, they may be ignored, resulting in recommendation results being too focused on popular news. Therefore, the study combines the UBCF algorithm to improve it. The overall structure diagram of the scheme is displayed in Fig. 4.

The model is mainly divided into two main branches, namely the UBCF branch and the IBCF branch. These two branches are independent of each other but work together, aiming to provide more comprehensive and accurate recommendations from both user and project perspectives. Firstly, there is the UBCF branch, whose main task is to utilize the relationship data between users to improve the accuracy. Specifically, the inputs of the UBCF branch include user-item rating data and user relationship data. After processing these data, the system starts calculating the strength of relationships between users. Then the system further calculates the fusion similarity of users. This step obtains a more comprehensive user similarity indicator by comprehensively considering the similarity of user ratings and the strength of social relationships. Based on this indicator, the system constructs a user similarity network that describes the similarity between users in terms of interests and social relationships. To further optimize the recommendation results, the system uses the Label Propagation network to perform clustering analysis on users. Through this method, the system can gather users with similar interests and social relationships together to form user clusters, as shown in Fig. 5.

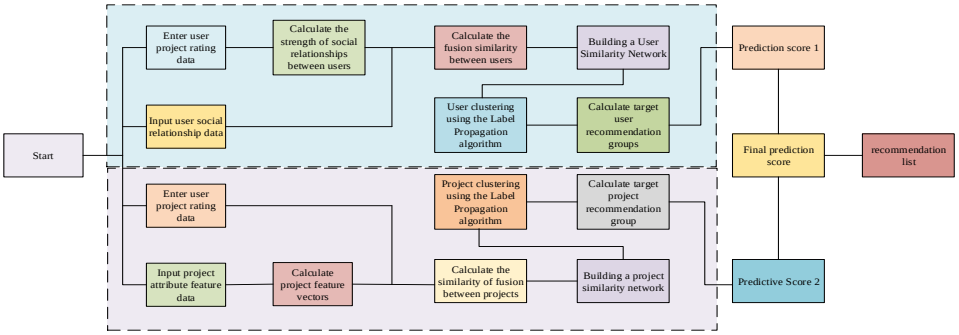



Fig. 4. Schematic diagram of news recommendation model structure combining IBCF algorithm and UBCF.

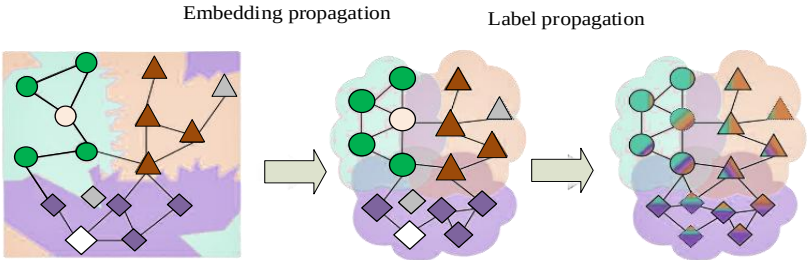



Fig. 5. Cluster analysis of users using the Label Propagation network.

The system identifies the user group that is most similar in interests and social relationships to the target user, namely the recommendation group. The UBCF branch calculates predicted scores based on this and rating data, reflecting the potential interest of the target user in the project. The IBCF branch utilizes project attribute feature data to improve recommendation accuracy. After processing user-project ratings and project attribute feature data, the system calculates project feature vectors and fuses similarity to obtain more comprehensive project similarity indicators. Due to the strong timeliness of news, traditional IBCF is unable to complete cold start recommendations when new projects appear. Therefore, the study adopts a new calculation method based on attribute similarity to solve this problem, as shown in Eq. (8).

$$Sim(I_1, I_2) = \beta Sim\_V(I_1, I_2) + (1-\beta)\,\mathrm{Si}\,m\_P(I_1, I_2) \tag{8}$$

In Eq. (8), $\beta$ represents the tuning parameter. $\mathrm{Si}\,m\_P$ represents the similarity of items considering user rating preferences. $Sim\_V$ represents the similarity of attributes between two items, as shown in Eq. (9).

$$Sim\_V(I_1, I_2) = \frac{\sum_{t=1}^{n} Sim(p_t, q_t)}{n} \tag{9}$$

In Eq. (9), $p_t$ stands for the $t$-th feature vector in project $I_1$. $q_t$ stands for the $t$-th feature vector in project $I_2$. $Sim(p_t, q_t)$ represents the similarity of the $t$-th feature vector between project $I_1$ and project $I_2$. To simplify the calculation, it can be expressed as Eq. (10).

$$Sim(p_t, q_t) = \frac{(\max_t - \min_t) - |\,p_t - q_t\,|}{\max_t - \min_t} \tag{10}$$

In Eq. (10), $\max_t$ stands for the maximum value of the $t$-th eigenvector. $\min_t$ represents the minimum value of the $t$-th feature vector. In news recommendation models, this component may be simple text data. Therefore, the similarity of $Sim(p_t, q_t)$ needs to be determined based on different types, as shown in Eq. (11).

$$Sim(p_t, q_t) = \begin{cases} 1/T & p_t \neq q_t \\ 1 & p_t = q_t \end{cases} \tag{11}$$

In Eq. (11), $T$ stands for the type of value under the $t$-th feature vector. Based on this indicator, a project similarity network is constructed, which describes the similarity between projects in terms of attributes and user evaluations. Similar to the UBCF branch, to optimize recommendation results, the IBCF branch uses a Label Propagation network to cluster items, forming a recommendation group. The predicted score is derived from the recommendation group and rating data, reflecting the user's interest in the project. UBCF and IBCF are fused to calculate the final prediction score, ensuring recommendation accuracy and diversity. The user recommendation groups is divided into three steps. The system generates a news recommendation list based on predicted scores, presenting the most relevant and interesting items to users, as shown in Fig. 6.

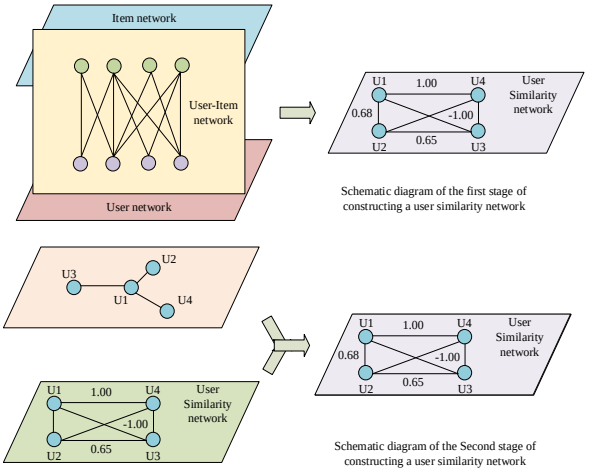



Fig. 6. Schematic diagram of the calculation process for user recommendation groups.

Firstly, based on the similarity of user rating preferences, the user-item bipartite graph (used to represent the preference relationship between users and items) is mapped to the original user similarity network. In the user-item bipartite graph, nodes are divided into two groups, one representing users and the other representing items. The second step is to use the Label Promotion network to aggregate user groups. Finally, similar users are grouped together to discover their group behavior patterns. The K-means is applied to calculate the user's belonging degree to the community, which requires calculating the category center and the center point of each cluster. Assuming $c_j$ represents the center of cluster $c_j$, the cluster center is shown in Eq. (12).

$$\min j \in (1,2,...,k) \| x_i - c_j \| 2 \tag{12}$$

In Eq. (12), $x_i$ represents sample $i$. The criterion function is shown in Eq. (13).

$$J = \sum i = 1n \min j \in (1,2,...,k) \| x_i - c_j \| 2 \tag{13}$$

In Eq. (13), $n$ represents the number of samples. $k$ represents clustering. The key to this method is to continuously adjust and optimize the center position of each category to ensure that they best represent the sample points in that category, thus forming clusters. As the number of users and news increases, data processing and storage can become a bottleneck. Given this, distributed database and cloud computing technology are used to disperse data to multiple nodes for storage and processing to improve data throughput and processing speed. When user and news numbers proliferate, similarity calculation and recommendation algorithms can become very time-consuming. Using parallel computing techniques, such as using the Apache Spark processing framework, to assign computing tasks to multiple processing units, thus accelerating algorithm execution and improving the scalability of the system. In order to improve the interactivity of personalized recommendations for online news, real-time user data collection is required. Research has adopted streaming distributed data collection technology for real-time user data collection. Based on the Apache Spark framework, configure hardware resources, install operating systems, and necessary software dependencies. The main reason for studying based on Apache Spark is its powerful distributed processing capabilities. Spark supports memory computing, reduces disk I/O operations, improves data processing speed, and is very suitable for real-time user data collection and analysis. Install and configure the ZooKeeper cluster for coordinating Spark jobs to ensure the normal operation of the server. Then assign sub server roles, divide the server into different roles based on system requirements and load balancing strategies, such as data extraction nodes, data processing nodes, etc., and study the use of HAProxy strategy. Create a Kinesis data collection queue again and establish a dedicated data collection queue to receive raw data obtained from the data source, ensuring that the data enters the system in an orderly manner. The next step is to classify the data flow, categorize the original data, and label the incoming data by user ID, news ID, or other attributes based on data type and source, in order to process specific data flows more efficiently in subsequent operations. Finally, establish an index for the stored data to improve the efficiency of subsequent queries and retrieval. Through this method, real-time user data collection and efficient processing can be achieved. By categorizing data streams and establishing indexes, the pertinence and retrieval efficiency of data processing can be improved, thereby enhancing the interactivity and personalization of news recommendations.

## IV. Performance Testing and Applicability Analysis of IBCF-UBCF Algorithm

This chapter is mainly divided into two sections. The first section mainly conducts a series of algorithm comparison analysis and performance testing on the proposed IBCF-UBCF. The second section mainly focuses on the application of the IBCF-UBCF model in practical news recommendation experiments.

### *A. Performance Testing of Personalized Recommendation Models for Online News*

To improve the quality of personalized recommendation content for online news, a new personalized recommendation algorithm for online news is designed by combining the IBCF algorithm and UBCF algorithm. To fully verify the excellent performance of the algorithm, the Collaborative Filtering (CF), Wisdom of the Crowd-based Recommendation (WCR), and Self-Attention Recommendation (SAR) are introduced to compare with the IBCF-UBCF algorithm, The above four algorithms are trained using the Microsoft News Dataset (MIND) and MSNBC.com dataset, respectively. The study took into account several characteristics of the sample, including historical behavioral data of users, the subject and type of news content, and users' social connections. Specifically, users' historical behavior describes their past clicks and comments on various types of news, reflecting their personal interests and preferences. The characteristics of news content, including title, keywords, publication time, etc., can help the algorithm understand the similarity between different news. In addition, the user's social relationship features are used to capture the interaction between users, and further enhance the personalization and accuracy of recommendations by analyzing the interaction between users in the social network. Fig. 7 the experimental results.

Fig. 7 shows the accuracy curves during the training process. From Fig. 7(a), in the MIND dataset, the IBCF-UBCF had the fastest convergence speed. After 140 iterations, it converged to 96.3%. The accuracy of WCR, SAR, and CF algorithms was slightly lower, at 90.3%, 85.4%, and 77.8%. From Fig. 7(b), the accuracy performance of the IBCF-UBCF didn't changed much in the MSNBC.com dataset. The accuracy of the other three algorithms varied significantly. The improved UBCF algorithm proposed in the study had strong generalization ability and high accuracy. To further verify the superiority of the proposed network news personalized book intelligent recommendation model based on the IBCF-UBCF, the root mean square error (RMSE) and training time of the four algorithms are shown in Fig. 8.

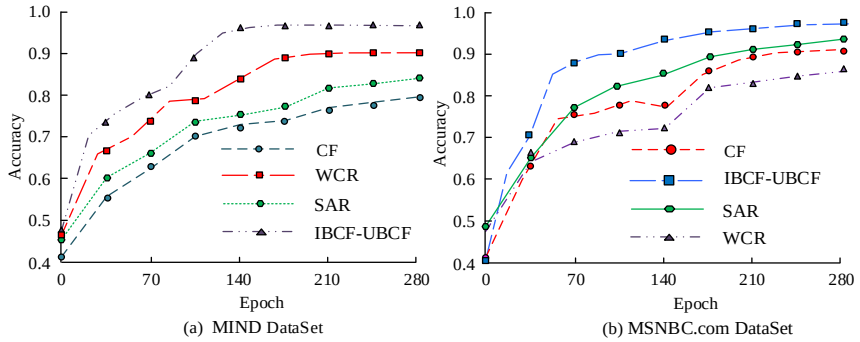



Fig. 7. Accuracy curves during the training process.

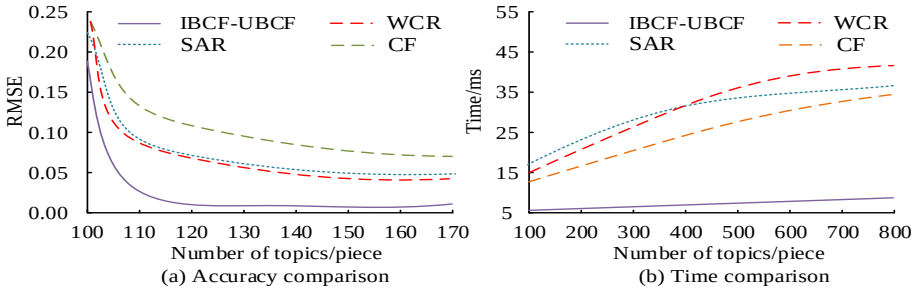



Fig. 8. Comparison results of root mean square error and running time.

Fig. 8(a) shows the RMSE comparison results of the four algorithms. The RMSE of the four algorithms decreased continuously with the increase of sample size. The minimum RMSE of the IBCF-UBCF was 0.010. The lowest RMSEs of WCR, SAR, and CF algorithms were 0.051, 0.053, and 0.068, respectively. Fig. 8(b) shows the running time. When the sample size was 800, the running time of the four algorithms was 6.3ms, 30.5ms, 35.4ms, and 38.9ms, respectively. In the above experimental results, the comparison results of the proposed algorithm on different data sets are different, which is due to the differences in the characteristics and structure of the data sets, such as the user behavior pattern, the diversity of news content and the degree of data sparsity. By combining UBCF and IBCF, the proposed algorithm can perform well in scenarios with strong user social influence, so it is more suitable for data sets with rich social network information. In addition, the performance of the algorithm can be fully utilized when the news content attributes in the data set are more diverse and the user's historical behavior records are sufficient. Conversely, in scenarios where data is sparse or social interaction is lacking, the effectiveness of the algorithm may be limited. To verify the effectiveness of each component in the IBCF-UBCF, ablation experiments are designed. Table II displays the experimental results.

TABLE II IBCF-UBCF ALGORITHM ABLATION EXPERIMENT

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| IBCF-UBCF | 0.000032 | 0.0057 | 0.0022 |
| WCR | 0.000145 | 0.0131 | 0.0069 |
| SAR | 0.000078 | 0.0091 | 0.0044 |
| CF | 0.000052 | 0.0056 | 0.0010 |
| Missing IBCF module | 0.000168 | 0.0173 | 0.0061 |
| Missing UBCF module | 0.000173 | 0.0121 | 0.0056 |

From the results presented in Table II, among numerous network news recommendation algorithms, the IBCF-UBCF had excellent performance. The values of mean square error (MSE), RMSE, and mean absolute error (MAE) were 0.000032, 0.0057, and 0.0022. These data are significantly superior to other algorithms, fully demonstrating the superiority of the IBCF-UBCF in network news recommendation tasks. Furthermore, to verify the effectiveness of each module in the IBCF-UBCF, ablation experiments are conducted. When the IBCF module was missing, the MSE, RMSE, and MAE were 0.000168, 0.0173, and 0.0061, indicating a decrease in recommendation performance. This indicates that the IBCF module plays a crucial role in the algorithm. Similarly, when the UBCF module was missing, the MSE, RMSE, and MAE values of the algorithm were 0.000173, 0.0121, and 0.0056, respectively, showing a certain performance decline. These two experiments further confirm the importance of the IBCF and UBCF modules in the IBCF-UBCF, both of which are indispensable and together ensure the high performance of the algorithm.

### B. *Application Analysis of IBCF-UBCF in Network News Recommendation Model*

The experiment repeatedly verifies the superiority of the IBCF-UBCF in the field of online news recommendation. To further prove its equally good performance in practical applications, it is applied in actual news recommendation software. The research method is compared with the methods proposed in references [22] and [23] to explore the resource consumption of each algorithm during operation. The CPU used in the experiment is Intel i5-2500K, and the experimental platform is Windows 10. The dataset used is the news recommendation data obtained from the ByteDance's official website. These data have been carefully cleaned, deweighted,

marked and annotated to ensure the quality and accuracy of the data. In the process of processing, we also paid special attention to the correlation of user behavior and news content, thus constructing a highly personalized news recommendation data set, namely, Personalized News Recommendation Datasets (PNRD). The experimental results are shown in Fig. 9.

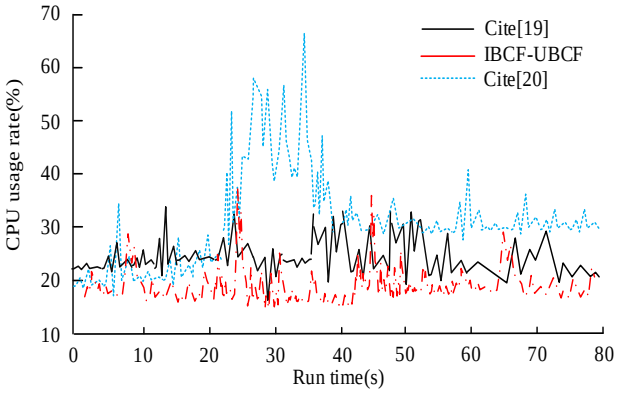



Fig. 9. The resource consumption of three algorithms in actual news recommendations.

From the graph, the proposed IBCF-UBCF had a relatively low CPU usage during system operation, with little fluctuation, maintaining a CPU usage rate of around 20. The performance of the algorithm proposed in research [23] was poor. Its CPU usage fluctuated greatly during the 10-30s period, and the average CPU usage during operation reached 30%. The performance of the method proposed in study [22] fell between the two, with an average CPU usage rate of 25% during runtime. In addition, the study also records the ROC curves of three models. Fig. 10 displays the results.

From the graph, the proposed IBCF-UBCF had the highest ROC curve, which fully demonstrated its outstanding performance among all the algorithms involved in the comparison. In addition, the area under the ROC curve of each algorithm, i.e. the AUC value, is experimentally calculated. The AUC value of the IBCF-UBCF was as high as 0.936, highlighting its superior news recommendation performance. In contrast, the AUC value of the reference [22] was 0.901, while the AUC of the reference [23] was 0.878, which once again proved the excellent performance of the IBCF-UBCF in news recommendation tasks. In addition, the experiment randomly interviews 1000 users in the age group (children, youth, middle-aged, quinquagenarian, old age), who evaluates the recommended content of the IBCF-UBCF algorithm using a percentage system, and compared with the proposed method in literature [23], the statistical results of the evaluation are shown in Fig. 11.

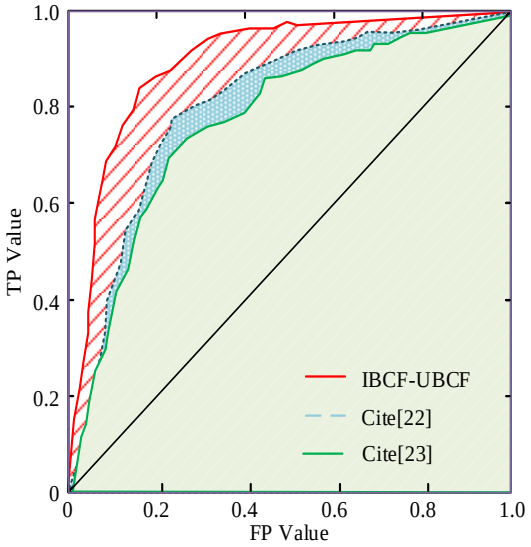
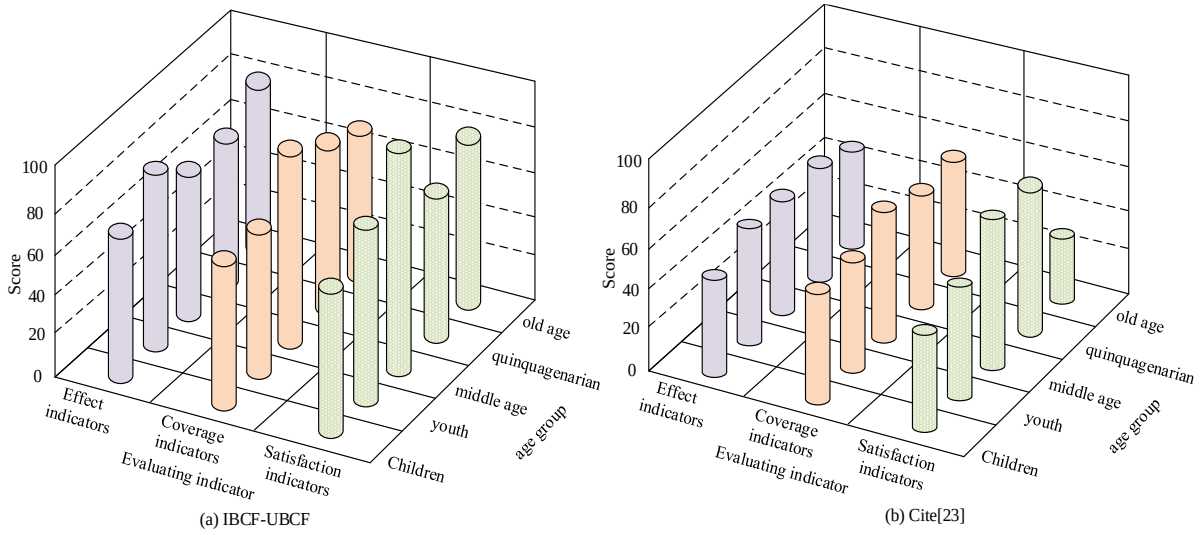



Fig. 10. ROC curves during the use of three algorithms.




(a) IBCF-UBCF (b) Cite[23]

Fig. 11. The score of individual indicators in the IBCF-UBCF.

From the provided chart data, it is evident that volunteers from different age groups have relatively high evaluations of the three key indicators of the news recommendation system - performance, coverage, and satisfaction. Especially in terms of performance indicators, the news recommendation system achieved a high score of 95.3, demonstrating its outstanding performance in news push. Not only do young users give it a high rating, but other age groups also give it a rating of 85 or above, indicating that the system can meet the needs of users of all age groups. In terms of coverage, the middle-aged population gave the highest rating, with an average score of 94.3 points. Volunteers from other age groups also received positive reviews, with an average score of over 93, indicating that the news recommendation system has done a fairly comprehensive job in content coverage. As for satisfaction, even for the lowest rated 50-year-old population, their score is above 80 points, indicating that users are generally satisfied with the system. However, the performance of the methods proposed in reference [23] is relatively low. In summary, the news recommendation system has received high recognition among users of different age groups. In addition, the study tested the performance of the system in low, medium and high load conditions, recording response time, throughput and resource utilization, School of Humanities and Law, Nanchang HangKong University, Nanchang 330063, China. Subsequently, the three load conditions were tested again by increasing the system resources to observe the impact of the increased resources on the system performance. The experimental results are shown in Table III.

TABLE III COMPREHENSIVE PERFORMANCE ANALYSIS OF ONLINE NEWS PERSONALIZED RECOMMENDATION SYSTEM

| Experimental group | Response time (ms) | Throughput (requests/second) | Resource utilization rate (%) |
|---|---|---|---|
| Low load | 50 | 1000 | 20 |
| Medium load | 80 | 800 | 30 |
| High load | 120 | 600 | 40 |
| Increase resources - low load | 40 | 1200 | 25 |
| Increase Resources - Medium Load | 65 | 1000 | 35 |
| Increase resources - high load | 90 | 800 | 45 |

Under low, medium, and high load conditions in the experimental group, as the load increases, the response time gradually increases while the throughput gradually decreases. This indicates that under high loads, the system's processing speed of requests slows down, and the number of requests it can process also decreases. The resource utilization rate increases with the increase of load, indicating that the system fully utilizes resources under high loads. When resources are increased, response time decreases, throughput improves, and resource utilization improves under low, medium, and high load conditions. This indicates that increasing resources can effectively improve system performance, enabling the system to respond to requests faster, process more requests, and utilize resources more efficiently. In summary, the table data shows the impact of load and resources on system performance, as well as the performance improvement that increasing resources can bring. This provides valuable reference information for system optimization and resource allocation. Validation measures were included in the study, and the results were compared with previous studies, as shown in Table IV.

TABLE IV RESULTS OF ALGORITHM PERFORMANCE VERIFICATION

| Reference | Method | Accuracy rate (%) | Recall rate (%) | RMSE |
|---|---|---|---|---|
| Mizgajski et al. [4] | Emotion perception recommendation system | 82.5 | 78.0 | 0.052 |
| Goyani et al. [5] | Combine collaborative filtering with content filtering | 80.3 | 75.5 | 0.063 |
| Symeonidis et al. [6] | User intent analysis | 83.1 | 80.2 | 0.049 |
| Research method | IBCF-UBCF algorithm | 96.3 | 91.5 | 0.010 |

Table IV shows the performance verification results of the proposed IBCF-UBCF algorithm compared with previous studies. As can be seen from the table, IBCF-UBCF algorithm is significantly superior to other methods in the accuracy rate (96.3%) and recall rate (91.5%), indicating that it achieves higher user satisfaction and relevant content recommendation ability in the recommendation system. At the same time, the root-mean-square error (RMSE) of the algorithm is only 0.010, indicating that its error in predicting user preferences is very small, which further proves its excellent performance. In contrast, the accuracy and recall rates of previous research methods were both below 85%, and RMSE values were generally higher than 0.05, reflecting their instability and potential limitations in handling recommendation tasks. These results fully demonstrate the effectiveness and superiority of the IBCF-UBCF algorithm in the field of personalized recommendation, and verify its potential in improving user experience and recommendation system performance.

## V. DISCUSSION

In order to evaluate the novelty of the proposed algorithm, the proposed IBCF-UBCF model was compared with other recommended algorithms (such as CF, WCR and SAR). By comparing the convergence rate, accuracy and RMSE, the performance of the proposed model was evaluated. The results show that the algorithm improved the accuracy and diversity of the recommendation. By evaluating the ability of the recommendation system to cover popular content, long tail content, diversity and personalization, we can determine whether the system can meet the interests and needs of different users. By considering user satisfaction indicators such as timeliness, user retention, user ratings, and user feedback, researchers are able to measure user satisfaction and acceptance of recommended results. Retest the three load conditions by increasing the system resources, and observe the effect of the increased resources on the system performance. The results show that the system realizes efficient data processing and storage, and effectively solves the bottleneck problem of data processing and storage. A comprehensive evaluation index system realizes the efficient data processing and storage, and improves the interactivity and personalization degree of the recommendation system.

The advantages of the study are that it effectively solve the data sparsity problem and improve the personalization of recommendations. In addition, the method realizes efficient data processing and storage through the flow of distributed data acquisition technology and cloud computing framework, which significantly improves the performance and response speed of the system. The disadvantage of research is that because the system mainly relies on regular calculations and updates, it may not reflect the latest interests of users in real time and the changes of news. Moreover, the average satisfaction of the model among middle-aged and elderly groups is relatively low, indicating that the system may need to be further optimized to better meet the needs of different age groups.

To overcome these defects, real-time data flow processing technology can be introduced in the future to realize just-in-time analysis of user behavior data, which can improve the real-time performance of the recommendation system and better capture the latest interests of users, such as the Apache Kafka technology adopted in literature [24]. Develop multimodal learning algorithms, combining user historical behavior and immediate feedback, and multi-dimensional features of news content to enhance the adaptability of the model to the needs of users of different ages. The user feedback mechanism is designed to allow users to evaluate the recommendation results, and then these feedback data is used to further train and optimize the algorithm to improve the relevance of recommendations and users' satisfaction, such as the scheme based on social relations and behavioral characteristics adopted in literature [25].

## VI. Conclusion

To provide readers with more accurate network news recommendation results, a new network news recommendation algorithm is designed by combining the IBCF and UBCF. In algorithm performance testing, the IBCF-UBCF had the fastest convergence speed, reaching convergence after 140 iterations, and finally converging to 96.3%. The accuracy of WCR, SAR, and CF algorithms was slightly lower, at 90.3%, 85.4%, and 77.8%, respectively. The improved UBCF proposed in the study had strong generalization ability and high accuracy. In addition, the RMSE of the four algorithms decreased continuously with the increase of sample size. The minimum RMSE of the IBCF-UBCF was 0.010. The lowest RMSE of WCR, SAR, and CF were 0.051, 0.053, and 0.068, respectively. The IBCF-UBCF proposed in the study had a relatively low CPU usage during system operation, with little fluctuation. It generally maintained a CPU usage rate of around 20. The performance of the algorithm proposed by the comparative study is poor. In the 10-30 second period, its CPU usage fluctuates greatly, and the average CPU usage reaches 30% during operation. The results of the satisfaction assessment of the volunteers showed that they scored an average of 85, 93 and 86 points on the model's performance indicators, coverage indicators and satisfaction indicators, respectively. These high scores indicate the effectiveness of the model in meeting the personalized needs of users and enhancing the experience of the recommendation system. The experimental results show that the proposed method is significantly superior to the existing recommendation algorithms in many performance indexes, demonstrating excellent performance and low resource consumption. In addition, through the introduction of real-time user data collection and distributed processing technology, the response speed and scalability of the recommendation system are improved, and the effectiveness of the research method in practical applications is verified. The proposed algorithm effectively overcomes the common problems of sparse data, cold start and insufficient diversity of recommendation in traditional personalized recommendation methods, and significantly improves the accuracy and user satisfaction of recommendation by comprehensively considering users' historical behaviors, social relations and news content characteristics.

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# Comparative Analysis of SVM, Naïve Bayes, and Logistic Regression in Detecting IoT Botnet Attacks

Apri Siswanto[1], Luhur Bayu Aji[2], Akmar Efendi[3], Dhafin Alfaruqi[4], M. Rafli Azriansyah[5], Yefrianda Raihan[6]
Informatics Department-Faculty of Engineering, Universitas Islam Riau, Pekanbaru, Indonesia[1, 3, 4, 5, 6]
Faculty Data Science and Information Technology, INTI International University, Malaysia[2]

***Abstract*—The rapid proliferation of Internet of Things (IoT) devices has significantly increased the risk of cyberattacks, particularly botnet intrusions, which pose serious security threats to IoT networks. Machine learning-based Intrusion Detection Systems (IDS) have emerged as effective solutions for detecting such attacks. This study presents a comparative analysis of three widely used machine learning classifiers—Support Vector Machine (SVM), Naïve Bayes (NB), and Logistic Regression (LR)—to assess their performance in detecting IoT botnet attacks. The experiment uses the BoTNeTIoT-L01 dataset, applying preprocessing techniques such as data cleaning, normalization, and feature selection to enhance model accuracy. The models are trained and evaluated based on standard performance metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. The results indicate that SVM outperforms the other classifiers in terms of detection accuracy and robustness, particularly in detecting malware based on PE files. These findings offer valuable insights into selecting suitable machine learning models for securing IoT environments. Future work will further explore integrating advanced feature selection techniques and deep learning models to improve detection performance.**

***Keywords*—IoT security; botnet detection; machine learning; intrusion detection system; comparative analysis; SVM; naïve bayes; logistic regression**

## I. Introduction

The rise of the Internet of Things (IoT) has revolutionized various industries by enabling seamless connectivity and automation. However, the rapid expansion of IoT networks has also introduced significant security challenges, particularly the increasing prevalence of botnet attacks. These attacks compromise vulnerable IoT devices, integrating them into a network of malicious bots that can be used for large-scale cyber threats such as Distributed Denial of Service (DDoS) attacks, data exfiltration, and unauthorized access. Traditional security mechanisms, such as signature-based intrusion detection systems (IDS) and firewalls, often fail to detect sophisticated and evolving IoT botnets due to their dynamic nature and high traffic volume [1], [2]. As a result, machine learning (ML)-based approaches have emerged as a promising solution for enhancing IoT security by identifying malicious patterns in network traffic. Despite the effectiveness of ML models, there is a need for a comprehensive comparison of their performance in detecting IoT botnet attacks [3], [4]. This study addresses this gap by analyzing and comparing three widely used ML classifiers—Support Vector Machine (SVM), Naïve Bayes (NB), and Logistic Regression (LR)—to determine their effectiveness in securing IoT environments.

Despite the growing adoption of machine learning techniques in IoT security, there remains a lack of recent comparative studies evaluating the performance of different classification algorithms in detecting IoT botnet attacks [5], [6]. While several studies have explored the application of SVM, NB, and LR individually, limited research has systematically compared their effectiveness using standardized evaluation metrics on modern IoT botnet datasets. Given the evolving nature of cyber threats, it is crucial to reassess the capabilities of these algorithms to determine their suitability for real-world IoT intrusion detection systems [7]. A thorough comparison can provide valuable insights into the strengths and limitations of each model, helping researchers and practitioners select the most appropriate approach for securing IoT environments [8]. This study aims to fill this gap by conducting a comprehensive performance analysis of SVM, NB, and LR in detecting IoT botnet attacks, considering key evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC [9].

The primary objective of this study is to analyze and compare the performance of three widely used machine learning algorithms—SVM, NB, and LR—in detecting IoT botnet attacks. To achieve this, the research utilizes a publicly available IoT botnet dataset and applies preprocessing techniques such as data cleaning, normalization, and feature selection to optimize model performance. Each algorithm is trained and tested using a standardized evaluation framework, with performance assessed based on key metrics, including accuracy, precision, recall, F1-score, and AUC-ROC [10], [11]. By conducting a systematic comparison, this study aims to identify the most effective classification model for IoT botnet detection, highlight the strengths and limitations of each approach, and provide recommendations for improving intrusion detection systems in IoT environments.

This study makes several key contributions to IoT security by conducting an in-depth comparative analysis of machine learning models for botnet attack detection. First, it utilizes a publicly available or private IoT botnet dataset, ensuring a realistic and diverse representation of attack patterns. Second, it evaluates the performance of three widely used classifiers—SVM, NB, and LR—using rigorous experimental settings and standardized performance metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. Through this evaluation, the study provides a clear assessment of each model's strengths and weaknesses in identifying IoT botnet attacks. Finally, based on the results, this research offers recommendations on the most suitable machine learning model for IoT intrusion detection, contributing valuable insights to

both researchers and practitioners in enhancing the security of IoT environments.

The rest of this paper is organized as follows: Section II reviews related work on IoT botnet detection and machine learning-based intrusion detection systems (IDS). Section III outlines the research methodology, including dataset selection, preprocessing techniques, model training, and evaluation metrics. Section IV presents the experimental results and a comparative analysis of the three machine learning models. Finally, Section V provides the conclusions of this study and discusses potential directions for future research.

## II. Related Work

### A. IoT Botnet Attack Detection

The rapid adoption of IoT devices has led to a significant increase in security threats, particularly in botnet attacks that exploit vulnerabilities in connected systems. Various approaches have been proposed to detect IoT botnet activities, including rule-based IDS, anomaly detection techniques, and machine learning-based classification methods. Traditional IDS typically relies on predefined signatures and heuristics to identify malicious traffic; however, they often struggle with zero-day attacks and the evolving behaviors of botnets [12]. Anomaly detection methods can identify new threats by detecting deviations from normal behavior, but they frequently suffer from high false positive rates, which can hinder their effectiveness in real-world applications [13]. Consequently, machine learning (ML) has garnered attention as a promising method for enhancing IoT security, given its ability to learn patterns from large-scale network traffic data and distinguish between normal and malicious activities [14].

### B. Machine Learning for Intrusion Detection in IoT

Supervised learning techniques, including SVM, NB, and LR, have been widely employed in IoT security applications. SVM is particularly noted for its robustness in high-dimensional spaces and its capability to handle non-linearly separable data, making it suitable for complex IoT environments [15]. NB, while computationally efficient, it operates under the assumption of feature independence, which may not always hold true in real-world network traffic data [16]. LR, a probabilistic model, is often utilized for binary classification tasks and offers interpretable decision boundaries, which can be advantageous in understanding the underlying decision-making process [17]. Prior studies have successfully applied these models to IDS, demonstrating promising results in identifying network-based attacks [18]. However, the comparative performance of these classifiers, specifically in the context of IoT botnet detection, remains an area that requires further investigation.

### C. Comparative Studies on ML-Based IDS

Several research works have explored the effectiveness of ML classifiers for intrusion detection. For instance, Gu et al. evaluated the performance of SVM and NB in detecting network anomalies, concluding that SVM achieved higher accuracy but required significant computational resources [19]. Similarly, Mohammed et al. compared LR with deep learning models for malware detection, highlighting the trade-offs between interpretability and classification performance [20]. However, these studies primarily focused on general cyber security threats and did not specifically address IoT botnet attacks. Furthermore, variations in datasets, preprocessing techniques, and evaluation metrics complicate the generalization of their findings [21].

### D. Research Gap and Contribution

The increasing ubiquity of IoT devices has raised significant concerns regarding the security of these systems, particularly regarding botnet attacks. Despite the growing body of literature on ML applications for detecting such attacks, there remains a dearth of comprehensive comparative studies systematically evaluating the performance of key classifiers, SVM, NB, and LR, tailored explicitly for IoT environments using contemporary datasets and standardized performance metrics. This presents a critical gap in understanding how these algorithms perform against each other in the specific context of IoT botnet detection.

Various studies have investigated different machine learning algorithms for intrusion detection within IoT frameworks. For instance, Al-Sarem et al., discussed various machine learning methods for botnet attack detection, including SVM and Naïve Bayes, but did not provide a direct comparative analysis between these classifiers within a unified experimental setup [6]. Additionally, Noor et al. highlighted that while many classifiers achieve high accuracy in other domains, systematic comparisons of SVM, NB, and LR in detecting IoT-specific botnet behaviors are severely lacking [22]. More directly related, Almomani et al. employed these classifiers for denial-of-service attack detection in IoT contexts and emphasized the need for rigorous and comparative evaluations across different algorithms [23].

Research conducted by Padhiar and Patel attempted to evaluate multiple machine learning algorithms for botnet detection, yet the focus was primarily on the efficacy of their proposed method without an in-depth comparative performance analysis of SVM, NB, and LR [24]. Furthermore, studies that analyze the comparative metrics of machine learning classifiers in other contexts indicate that a focused comparative study for IoT botnet detection is necessary. For instance, Das et al. demonstrated notable variances in accuracy and precision among several classifiers, including NB, SVM, and LR, in different classification tasks [25]. A similar comparative effort focusing on IoT botnet detection would clarify the strengths and weaknesses inherent in each algorithm regarding detection efficiency and accuracy.

In summary, the existing literature highlights the prevalence of individual algorithm studies but points out a void in systematic, comparative research involving SVM, NB, and LR in the context of IoT botnet detection. Such a study would not only enhance the understanding of which classifier effectively identifies botnet traffic but also set a precedent for applying standardized metrics to evaluate machine learning techniques across different cyber threat domains. This study aims to fill this gap by conducting a comprehensive performance analysis of these three classifiers using key evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. The findings of this research will provide insights into the suitability of different ML models for real-world IoT security applications and contribute to the development of more robust intrusion detection systems.

## III. RESEARCH METHOD

### A. Dataset

To evaluate the performance of machine learning models in detecting IoT botnet attacks, this study utilizes a publicly available IoT botnet dataset. Commonly used datasets for network intrusion detection include CTU-13, UNSW-NB15, and Bot-IoT, each containing labeled traffic data distinguishing between normal and malicious activities. Among these, the Bot-IoT dataset is particularly relevant, as it provides a comprehensive set of network traffic logs, including botnet-related attacks such as Distributed Denial of Service (DDoS), data exfiltration, and reconnaissance activities Meidan et al. [26] Injadat et al. [27]. The dataset contains various network features, such as packet size, flow duration, source and destination IP addresses, and protocol types, which serve as input for the classification models [28].

### B. Data Preprocessing

The dataset undergoes several preprocessing steps before training the machine learning models to enhance classification accuracy. First, data cleaning is performed to remove duplicate records, missing values, and inconsistencies, ensuring the integrity of the dataset [29]. Next, normalization is applied to standardize numerical features, ensuring that all attributes are within the same scale to prevent bias during training [30]. Additionally, feature selection is conducted to retain the most relevant attributes while reducing dimensionality, which improves computational efficiency. Techniques such as correlation-based filtering and Principal Component Analysis (PCA) are employed to identify and retain high-impact features [31]. The final preprocessed dataset is split into training and testing sets for model evaluation.

### C. Machine Learning Models

This study compares the performance of three widely used supervised learning algorithms: SVM, NB, and LR. SVM is a robust classifier that constructs an optimal decision boundary by maximizing the margin between different classes, making it particularly effective for high-dimensional datasets. However, its computational complexity may pose challenges when dealing with large-scale IoT traffic data [32]. NB, a probabilistic classifier based on Bayes' theorem, assumes feature independence and is computationally efficient, making it suitable for real-time applications. Despite its speed, the accuracy of NB may be affected by the independence assumption, which does not always hold in real-world network traffic data [33]. LR, a statistical model used for binary classification, estimates the probability of an instance belonging to a particular class using a sigmoid function. While simple and interpretable, its performance may be limited when handling complex, nonlinear attack patterns [33].

### D. Experimental Setup

The dataset is split into 80% training and 20% testing to assess the generalization capabilities of the models. Additionally, 10-fold cross-validation is performed during training to ensure robust performance assessment and prevent overfitting. Each machine learning model undergoes hyperparameter tuning to optimize its classification performance. For SVM, kernel functions such as linear, radial basis function (RBF), and polynomial are tested to determine the best decision boundary for separating normal and malicious traffic. In the case of Naïve Bayes, both Gaussian and Multinomial variants are explored, depending on the nature of the feature distributions. For Logistic Regression, L1 and L2 regularization techniques are applied to prevent overfitting and improve model generalization. The models are implemented using Python's scikit-learn library, leveraging optimized libraries to enhance computational efficiency [34].

### E. Evaluation Metrics

Five key evaluation metrics comprehensively assess model performance: accuracy, precision, recall, F1-score, and AUC- ROC. Accuracy measures the overall correctness of the classification, providing a general assessment of model effectiveness. Precision evaluates the proportion of correctly predicted positive instances, ensuring that false positives are minimized. Recall assesses the model's ability to correctly identify actual botnet attacks, which is critical for intrusion detection systems. F1-score, as the harmonic mean of precision and recall, provides a balanced measure when there is an uneven class distribution. Lastly, AUC-ROC (Area Under the Receiver Operating Characteristic Curve) quantifies the classifier's ability to distinguish between botnet and normal traffic across different threshold values [35]. By analyzing these metrics, this study aims to determine the most effective machine learning model for IoT botnet detection, offering insights into their suitability for real-world intrusion detection applications. These metrics comprehensively assess each model's strengths and weaknesses in detecting IoT botnet attacks. The evaluation results will determine the most effective machine learning approach for intrusion detection in IoT environments. For more details on the research method stages, see Fig. 1.

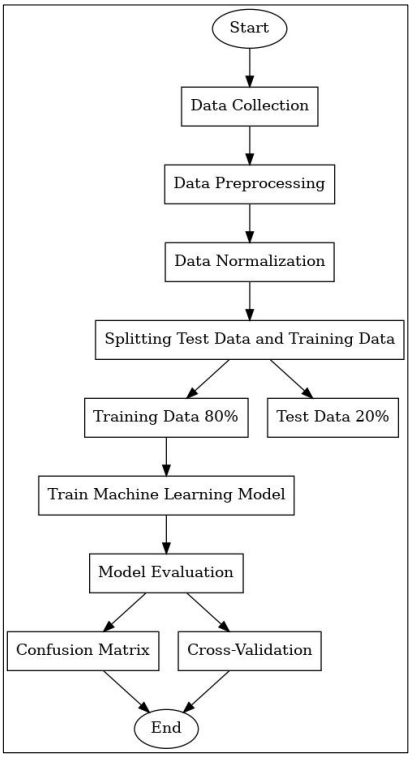


Fig. 1. Research steps.

## IV. RESULTS

### A. Experimental Results

The performance of the three machine learning models- SVM, Naïve Bayes (NB), and Logistic Regression (LR)—was evaluated using accuracy, precision, recall, F1-score, and AUC- ROC metrics. Table I summarizes the comparative performance of each model based on the test dataset.

TABLE I. THE EXPERIMENTAL RESULTS

| Model | Accuracy | Precision | Recall | F1-Score | AUC-ROC |
|---|---|---|---|---|---|
| SVM | 95.2% | 94.8% | 96.1% | 95.4% | 96.7% |
| NB | 89.6% | 88.3% | 90.7% | 89.5% | 91.2% |
| LR | 91.8% | 91.2% | 92.1% | 91.6% | 92.9% |

### B. Confusion Matrix

Confusion matrices were employed to further illustrate the classification performance of each model by detailing the correctly and incorrectly classified instances. Additionally, Receiver Operating Characteristic (ROC) curves were plotted to evaluate the trade-off between the true positive rate and false positive rate. Among all models, the Support Vector Machine (SVM) exhibited the highest Area Under the ROC Curve (AUC- ROC), indicating superior capability in distinguishing between IoT botnet traffic and normal network activity.

As a standard evaluation metric, the confusion matrix enables a comprehensive assessment by comparing predicted class labels against actual ground truth values, thereby highlighting classification accuracy and misclassification patterns. Fig. 2 presents the confusion matrices of the Naïve Bayes (NB), Logistic Regression (LR), and SVM classifiers. The SVM achieved the best performance with the lowest number of false negatives (FN = 7) and false positives (FP = 17), demonstrating high precision in detecting both positive and negative classes. The LR model also showed competitive performance (FN = 71, FP = 9), offering a balanced trade-off between accuracy and computational efficiency. Conversely, the NB classifier yielded the highest FN count (208), indicating a frequent failure to detect botnet attacks and suggesting limited suitability for high-accuracy intrusion detection scenarios. Overall, SVM emerges as the most effective classifier when maximizing detection accuracy of malicious traffic is a primary requirement.

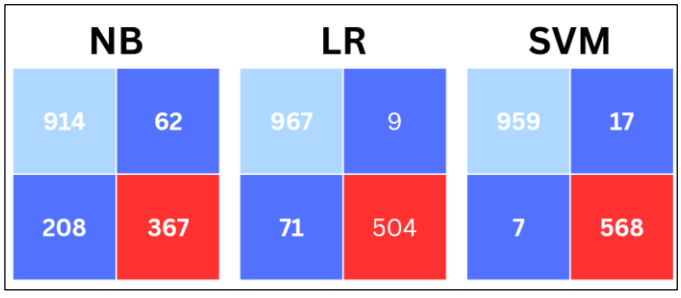


Fig. 2. Comparison of the confusion matrix of NB, LR, and SVM.

### C. Cross Validation

Cross-validation was conducted to evaluate the models' consistency across different data splits. The average performance scores obtained from 10-fold cross-validation are:

- LR Model: Mean score = 0.95 (95%)
- SVM Model: Mean score = 0.92 (92%)
- NB Model: Mean score = 0.79 (79%)

These results reinforce the robustness and generalizability of each model. Fig. 3 illustrates the comparison of mean cross- validation scores.

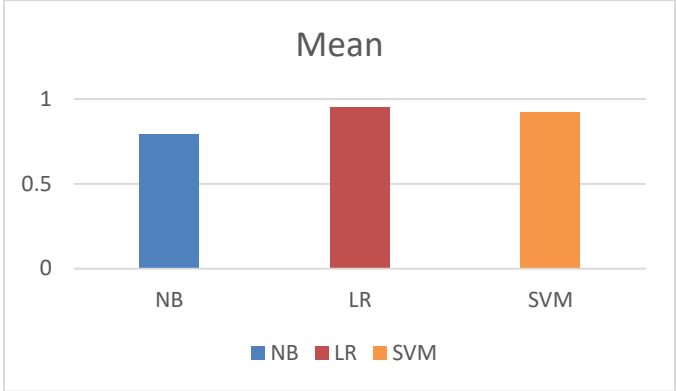


Fig. 3. Cross validation results.

## V. DISCUSSION

The SVM demonstrated the best overall performance among the three evaluated models, achieving the highest accuracy (95.2%) and recall (96.1%). These results suggest that SVM is highly effective in correctly identifying IoT botnet attacks. Its superior performance can be attributed to its ability to handle high-dimensional feature spaces and construct optimal decision boundaries. However, despite its accuracy, the high computational complexity of SVM presents a challenge for real- time applications, particularly in resource-constrained IoT devices.

In contrast, LR did not outperform SVM in accuracy but exhibited a favorable balance between classification performance (91.8% accuracy) and computational efficiency. Due to its simple mathematical foundation and lower computational requirements, LR is a viable option for real-time intrusion detection systems, especially in edge or embedded environments where latency and resource limitations are critical factors.

While computationally efficient, NB achieved the lowest performance among the three models, with an accuracy of 89.6% and the highest number of false negatives (208), as indicated by the confusion matrix. This performance drawback is likely caused by the algorithm's assumption of conditional independence between features, which is often violated in complex network traffic patterns. Despite this limitation, NB remains suitable for scenarios prioritizing fast inference and minimal computational cost over high detection accuracy.

To ensure robust and unbiased evaluation, all models were assessed using k-fold cross-validation, which divides the dataset into multiple subsets for iterative training and testing. The results from cross-validation revealed that the LR model consistently achieved the highest average performance across folds, suggesting strong generalization capabilities. Although SVM slightly trailed LR in fold-wise averages, it maintained high overall accuracy. In contrast, NB showed the most significant variability in performance, reaffirming its limited suitability for complex classification tasks in IoT security contexts.

These findings underscore the importance of selecting machine learning models based on the specific constraints of the IoT deployment environment. SVM is recommended for offline or centralized processing scenarios where accuracy is the primary concern and computational resources are sufficient. Conversely, LR and NB are more suitable for real-time detection in on-device or edge computing settings, where lightweight and low-latency models are essential.

Given the strengths and limitations of each model, a hybrid architecture is worth exploring. Such an approach could employ SVM for periodic offline analysis and LR or NB for real-time, on-device detection. Furthermore, future work may investigate ensemble or hybrid learning strategies to combine the predictive power of multiple algorithms, aiming to optimize both accuracy and efficiency in intrusion detection systems tailored for IoT environments.

In conclusion, this study provides a comparative analysis of classical machine learning algorithms applied to detect IoT botnet attacks. The empirical findings offer valuable insights into model suitability across different operational contexts, thereby contributing to developing scalable, adaptive, and effective cybersecurity solutions in the IoT domain.

## VI. Conclusion

This study presented a comparative analysis of SVM, NB, and LR in detecting IoT botnet attacks. Based on the experimental results, SVM demonstrated the highest accuracy (95.2%) and recall (96.1%), making it the most effective model for identifying botnet attacks. However, its computational complexity limits its feasibility for real-time intrusion detection on resource-constrained IoT devices. Logistic Regression provided a balanced trade-off between performance and efficiency, while Naïve Bayes, though the fastest model, showed lower accuracy due to its feature independence assumption. These findings suggest that model selection should consider detection accuracy and execution speed depending on the deployment environment.

Despite its contributions, this study has certain limitations. The performance of the models was evaluated using a single dataset, which may not fully capture the diversity of real-world IoT botnet attacks. Additionally, hyperparameter tuning was limited, and more advanced optimization techniques could further improve model performance. Future research could explore feature selection methods to enhance classification accuracy and reduce computational costs. Furthermore, implementing ensemble learning techniques, such as combining multiple classifiers, may provide more robust detection capabilities. Finally, testing these models on real-time network traffic in a dynamic IoT environment would be essential to validate their effectiveness against evolving cyber threats.

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# Bibliometric and Content Analysis of Large Language Models Research in Software Engineering: The Potential and Limitation in Software Engineering

Annisa Dwi Damayanti[1], Hamdan Gani[2]*, Feng Zhipeng [3], Helmy Gani[4],
Sitti Zuhriyah[5], Nurani[6], St. Nurhayati Djabir[7], Nur Ilmiyanti Wardani[8]
Department of Environmental Engineering, Faculty of Engineering, Hasanuddin University, Makassar, Indonesia[1]
Department of Machinery Automation System, ATI Makassar Polytechnic, Makassar, Indonesia[2, 7]
School of Culture Creativity and Media, Hangzhou Normal University, Hangzhou, Zhejiang, China [3]
Department of Industrial Hygiene, Faculty of Public Health, Occupational Health and Safety,
Makassar College of Health Sciences, Indonesia[4]
Department of Computer System, Universitas Handayani Makassar, Makassar, Indonesia[5]
Department of Information Systems and Technology, Institut Teknologi dan Bisnis Nobel Indonesia,
Jl. Sultan Alauddin No.212, Makassar and 90221, Indonesia[6]
Department of Informatics Engineering, Universitas Handayani Makassar, Makassar, Indonesia[8]

***Abstract*—Large Language Models (LLM) is a type of artificial neural network that excels at language-related tasks. The advantages and disadvantages of using LLM in software engineering are still being debated, but it is a tool that can be utilized in software engineering. This study aimed to analyze LLM studies in software engineering using bibliometric and content analysis. The study data were retrieved from Web of Science and Scopus. The data were analyzed using two popular bibliometric approaches: bibliometric and content analysis. VOS Viewer and Bibliometrix software were used to conduct the bibliometric analysis. The bibliometric analysis was performed using science mapping and performance analysis approaches. Various bibliometric data, including the most frequently referenced publications, journals, and nations, were evaluated and presented. Then, the synthetic knowledge method was utilized for content analysis. This study examined 235 papers, with 836 authors contributing. The publications were published in 123 different journals. The average number of citations per publication is 1.44. Most publications were published in Proceedings International Conference on Software Engineering and ACM International Conference Proceeding Series, with China and the United States emerging as the leading countries. It was discovered that international collaboration on the issue was inadequate. The most often used keywords in the publications were "software design," "code (symbols)," and "code generation." Following the content analysis, three themes emerged: 1) Integration of LLM into software engineering education, 2) application of LLM in software engineering, and 3) potential and limitation of LLM in software engineering. The results of this study are expected to provide researchers and academics with insights into the current state of LLM in software engineering research, allowing them to develop future conclusions.**

***Keywords*—Large Language Models; LLM; software engineering; bibliometric; content analysis**

## I. Introduction

Coupled with Generative Pre-trained Transformers, Large Language Models substantially advance natural language processing. ChatGPT, a cutting-edge conversational language model noted for its user-friendly interface, has attracted significant interest due to its advanced capacity to deliver human-like responses in various conversational scenarios. OpenAI has created an impressive conversational artificial intelligence (AI)-based language model known as the Chat Generative Pre-Trained Transformer (ChatGPT). On November 30, 2022, OpenAI released the ChatGPT GPT 3.5 series for free, followed by the premium version, GPT-4, on March 14, 2023 [1]. Additionally, other well-known LLMs include Google's Gemini, Microsoft Copilot, Meta's LLaMA, Anthropic's Claude, and Mistral AI's models [2].

The integration of this sophisticated technology in software engineering remains a subject of debate among stakeholders. Nevertheless, it holds potential for incorporation into the software engineering workflow [3]. Rahmaniar [4], suggests that more research should be conducted on LLM's effects and potential contributions to software engineering tasks such as code generation, bug fixing, and design decisions. LLMs have the potential to transform the software engineering sector by impacting various software development tasks, including code evolution and software testing [5].

Bibliometric research in software engineering is becoming increasingly popular [6]. According to their definition, bibliometrics is the study of a research issue using mathematical and statistical techniques based on bibliographic sources. The method of gathering and analyzing bibliometric data on a large scale allows bibliometric analysis to provide comprehensive details about the evolving patterns and intellectual structure of a research topic or discipline [7].

Bibliometric analysis comprises two techniques: scientific mapping and performance analysis [7]. Performance analysis examines how well individuals, organizations, and nations perform regarding research and publications [8]. Scientific mapping helps study scientific domains by revealing their structure and dynamics [9]. This study chose bibliometric analysis for our investigation because it can efficiently detect patterns and trends in the literature, highlight necessary studies and writers, and identify trends and topics for future research.

While previous bibliometric studies have examined the use of Large Language Models (LLMs) in fields such as public health, education, social sciences, and medicine, no such analysis has been conducted specifically in software engineering [10] to [16]. Existing research indicates that the application of LLMs in software engineering is still in its early stages. A detailed bibliometric analysis in this field is needed to identify key contributors, trends, and geographic activity, as well as to better understand the evolving potential and limitations of LLMs in software engineering.

The goal of this paper is to provide a bibliometric analysis of LLM studies in software engineering. The findings of our analysis provide information on the following issues:

*1)* What is the monthly distribution of publications on LLM?

*2)* What are the top five most cited publications in the LLM field?

*3)* Who are the top five most cited authors in the LLM field?

*4)* What are the dynamics of publications on LLM in the literature (journals and countries)?

*5)* What are the keywords most commonly used in publications on LLM?

*6)* Which themes emerged after the content analysis of LLM research?

## II. Literature Review

Previous research has explored bibliometric analyses on the usage of LLM in public health [10], education [11], social science [12], and medicine [13]. However, no bibliometric analysis of LLM has been performed in software engineering. A scoping study on applying an LLM in software engineering revealed that LLM research was in its early phases [14], [15]. Marques et al. [16] investigated the role of LLM in software requirements engineering, an essential aspect of software engineering. They discovered that the possibilities and limitations of LLM in software engineering are still developing and in their early phases. A detailed bibliometric analysis of LLM in software engineering can provide academics and stakeholders with an overview of the study. This research can assist in identifying the field's most prolific authors, countries, and scientific trends. In this case, bibliometric analysis could lead us to explore the potential and limitations of LLM in the software engineering field.

## III. Method

### A. Search Strategy

The flowchart of the research methodology is shown in Fig. 1. Web of Science and Scopus are the two most commonly utilized databases in bibliometric studies [17]. Data sources for this study included Scopus (Elsevier; https://www.scopus.com/) and Web of Science (Clarivate; https://www.webofscience.com/wos). The search strategy was designed as follows: "(TITLE-ABS-KEY ("Large Language Model" OR ChatGPT OR LLM OR Chatbot OR OpenAI OR Gemini OR Copilot)) AND (TITLE-ABS-KEY ("Software Engineering" OR "Software Development"))." The search was carried out on July 17, 2024. The search criteria were "article title, abstract, keywords" and publications on LLM in software engineering. There were no exclusion criteria. The search retrieved 529 studies from the two databases. After deleting 80 duplicate publications, 214 were reviewed using the inclusion criteria, resulting in 235 papers for bibliometric analysis.

### B. Bibliometric Methodology

Bibliometric analysis examines the performance of research elements, such as articles, authors, journals, keywords, and nations, and visualizes their intellectual, conceptual, and social structures through mapping methodologies [18]. In our work, the bibliometric methodology included performance analysis and scientific mapping techniques. The parameters for performance analysis were the number of articles and citations. Co-occurrence analysis was employed for scientific mapping [7].

Before data analysis, Scopus and Web of Science data were automatically combined using the RStudio IDE. The file was downloaded in BibTex format from Scopus and Web of Science, then updated in RStudio using R script code to produce a "database.csv" file (Source Code: Appendix). The data for this investigation was analyzed using VOS viewer version 1.6.20 (Leiden University, Netherlands, https://www.vosviewer.com) and Bibliometrix version 4.3.0 (University of Naples Federico II, https://www.bibliometrix.org). The VOS viewer allows users to observe things as well as their connections. "Items" are noteworthy objects, such as publications or researchers, while "links" represent the connections between these items. The VOS viewer establishes a correlation or relationship between two things. The stronger the link between the components, the greater the Total link strength (TLS), represented by a positive numerical value. On a map, things can be arranged into groups that form clusters. The weights applied to each item in network visualization represents its relative importance. The size of the circles or labels representing the object is strongly related to its weight; the more significant the circle or label representing an item, the heavier the item. This strategy simplifies understanding of the picture's components' relevance and relationships [8].

Bibliometrix is an open-source bibliometric software developed in R (The Comprehensive R Archive Network,

https://cran.r-project.org) [19]. After installing the Bibliometrix R package, the Bibliometrix web interface was accessible with the executed code "bibliometrix::biblioshiny ()". Bibliometrix was used to investigate publishing data (total citations, average citations, etc.) and international collaboration between countries.

### C. Content Analysis

Bibliometric analysis is an accurate method for recognizing the many information clusters that may appear in the literature. Klarin [18] developed the guideline for the knowledge synthesis approach used in content analysis. The approach consists of the following steps:

*1)* Research publications on LLM and Software Engineering are compiled.

*2)* Publications are categorized into themes depending on author keywords. Co-occurrence keyword analysis contains the results of this stage. Then, this study analyzes and characterizes the relationships between codes within each cluster in Section Co-occurrence keyword analysis."

*3)* Identify categories and assign theme names to clusters. Content Analysis shows the results of this stage.

*4)* The qualitative analysis generates a list of topics as output. Table III shows the results of all processes.

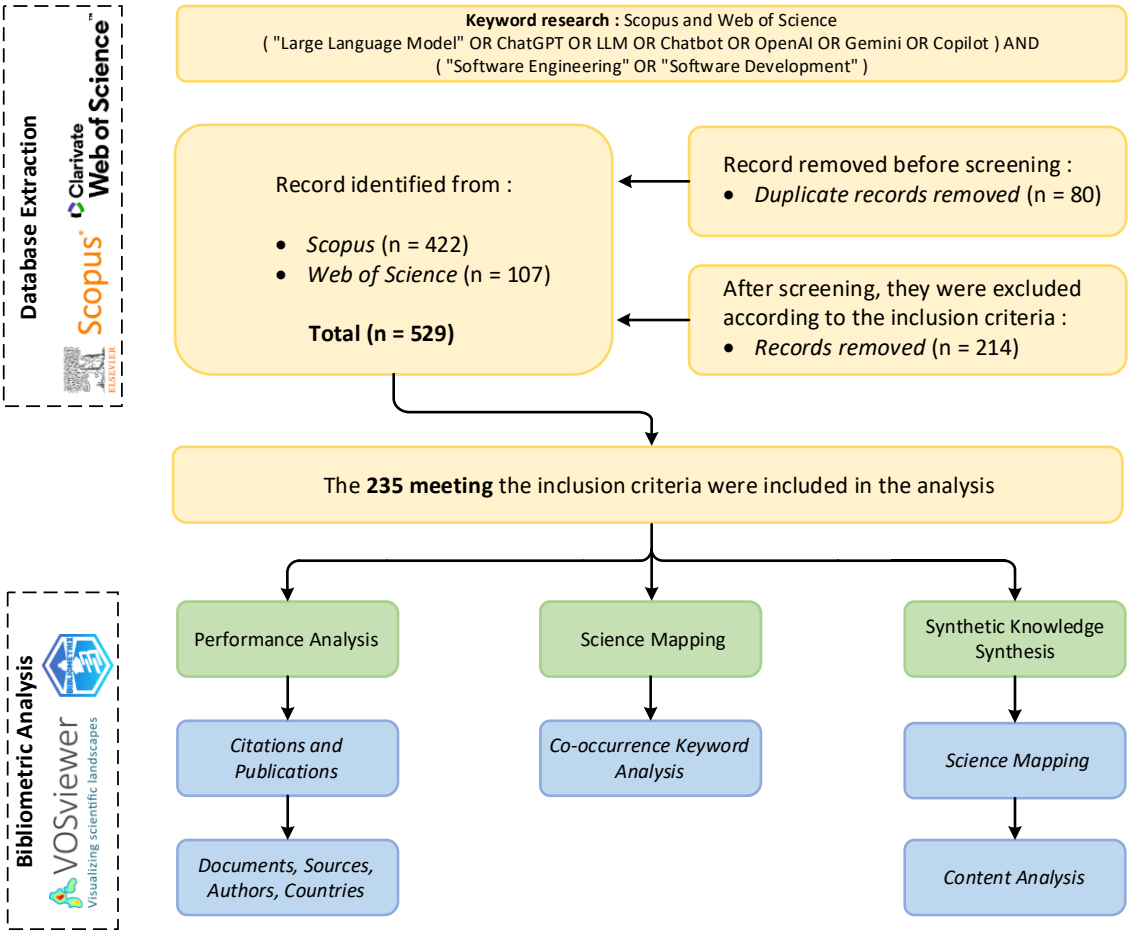


Fig. 1. Research methodology.

## IV. Results

### A. Publication Characteristics

Since ChatGPT was released on November 30, 2022, the publication distributions by month shown in Fig. 2, include publications published between January 2023 and June 2024. The analysis included 235 publications. The majority of the publications were published in April 2024. The publications comprised 51 articles, 138 conference papers, 39 proceeding papers, 3 reviews, 3 book chapters, and 1 lecture note. These papers, which had 836 authors, appeared in 123 different journals. The average number of citations was 1.44.

This analysis discovered that most articles were not research articles but conference and proceeding papers. In particular, scoping review research on LLM conducted on software engineering found that nearly one-quarter of the publications were "article" studies. This indicates that the research is still in its early stages. LLM, such as ChatGPT, is a new AI technology in software engineering [16].

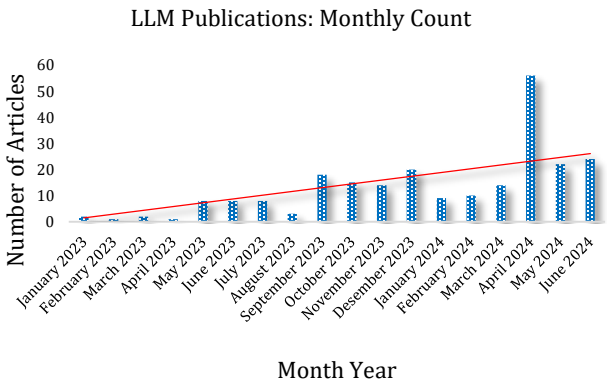


Fig. 2. Distribution of publications by months.

Since publications are published almost monthly, it is reasonable to expect future growth in LLM and software engineering studies.

### B. Top 10 Most Cited Publications and Authors

The most cited publication (Table I) discusses how ChatGPT can be used in software engineering to translate, create, and autocomplete code [20]. The second most cited work investigates the use of few-shot training with the GPT Codex model, demonstrating that it outperforms state-of-the-art models in code summarization while exploiting limited, project-specific data, emphasizing its importance in software engineering (Sobania et al., 2022). The research discovered that Copilot boosts software development productivity as measured by code-generated lines. The third most referenced work investigates the application of LLM in software engineering education and discusses improving software engineering education by personalizing learning experiences. They also emphasize the importance of modifying software engineering programs to match evolving software engineer profiles [21].

TABLE I. MOST CITED PUBLICATIONS AND AUTHORS

| No | Title | Publication Type | Authors | Journal | Number of Citation (Scopus) | Google Scholar Citation Count |
|---|---|---|---|---|---|---|
| 1. | The Programmer's Assistant: Conversational Interaction with A Large Language Model for Software Development | Conference Paper | (Ross et al., 2023) | International Conference on Intelligent User Interfaces, Proceedings IUI | 72 | 176 |
| 2. | Few-Shot Training LLMs for Project-Specific Code-Summarization | Conference Paper | [35] | ACM International Conference Proceeding Series | 27 | 121 |
| 3. | How ChatGPT Will Change Software Engineering Education | Proceedings Paper | [21] | Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education, ITICSE 2023, Vol 1 | 25 | 68 |
| 4. | GitHub Copilot AI Pair Programmer: Asset or Liability? | Article | [36] | Journal of Systems and Software | 24 | 241 |
| 5. | Generative AI for Software Practitioners | Article | [37] | IEEE Software | 20 | 97 |
| 6. | Towards Human-Bot Collaborative Software Architecting with ChatGPT | Proceedings Paper | [22] | 27th International Conference on Evaluation and Assessment in Software Engineering, EASE 2023 | 12 | 110 |
| 7. | Investigating Code Generation Performance of ChatGPT with Crowdsourcing Social Data | Proceedings Paper | [38] | 2023 IEEE 47th Annual Computers, Software, and Applications Conference, COMPSAC | 10 | 84 |
| 8. | Exploring The Implications of OpenAI Codex on Education for Industry 4.0 | Conference Paper | [39] | Studies in Computational Intelligence | 9 | 16 |
| 9. | Natural Language Generation and Understanding of Big Code For AI-Assisted Programming: A Review | Review | [40] | Entropy | 9 | 40 |
| 10. | Large Language Model Assisted Software Engineering: Prospects, Challenges, and A Case Study | Conference Paper | [41] | Lecture Notes in Computer Science | 6 | 48 |

The sixth most cited publication investigates how Software Development Bots, specifically ChatGPT, might help architecture-centric software engineering (ACSE) processes. It explores the problems of ACSE and proposes using ChatGPT to combine human experience with AI-powered decision support. The paper also describes a case study in which a novice architect collaborated with ChatGPT to design a service-based software system. The authors suggest future research to collect more empirical evidence on the productivity and socio-technical aspects of using ChatGPT in software architecture [22].

The most cited publications generally discuss ChatGPT's use in software engineering for tasks such as code translation, generation, and autocomplete. Another study shows that GPT Codex outperforms state-of-the-art models in code summarization using project-specific data via few-shot training. Generative AI, such as ChatGPT, is also being considered to improve software engineering education and change curriculum. A study further emphasizes ChatGPT's importance in architecture-centric software engineering (ACSE) by supporting new architects and recommends additional research on productivity and socio-technical issues.

### C. Most Productive Journals

The most productive journals in terms of the number of publications in the field of LLM are Proceedings - International Conference on Software Engineering (n = 27), ACM International Conference Proceeding Series (n = 20), Lecture Notes in Computer Science (n = 10), Proceedings - 2023 38TH IEEE/ACM International Conference on Automated Software Engineering, ASE 2023 (n = 9) and IEEE Transactions on Software Engineering (n = 6), respectively (Table II).

In the remaining journals, one or two articles were published. The most productive journals in terms of the number of citations are Proceedings - International Conference on Software Engineering (n = 54), ACM International Conference Proceeding Series (n = 33), and Lecture Notes in Computer Science (n = 15), respectively.

TABLE II. THE MOST PRODUCTIVE SOURCES

| No | Journal | N*) | Total Citation | H-Index | G-Index |
|---|---|---|---|---|---|
| 1 | Proceedings - International Conference on Software Engineering | 27 | 9 | 1 | 2 |
| 2 | ACM International Conference Proceeding Series | 20 | 29 | 1 | 5 |
| 3 | Lecture Notes in Computer Science | 10 | 12 | 2 | 3 |
| 4 | Proceedings - 2023 38TH IEEE/ACM International Conference on Automated Software Engineering, ASE 2023 | 9 | 8 | 2 | 2 |
| 5 | IEEE Transactions on Software Engineering | 6 | 8 | 2 | 2 |
| 6 | Proceedings - 2023 IEEE International Conference on Software Maintenance and Evolution, ICSME 2023 | 5 | 3 | 1 | 1 |
| 7 | IEEE Software | 4 | 22 | 2 | 4 |
| 8 | Journal of Systems and Software | 4 | 24 | 1 | 4 |
| 9 | Lecture Notes in Business Information Processing | 3 | 5 | 2 | 2 |
| 10 | Automated Software Engineering | 3 | 1 | 1 | 1 |

Note. (*) Sources that published at least two publications were listed.

The fact that the Proceedings - International Conference on Software Engineering has the most citations implies that research in this discipline is well-received in academic circles. The article "The Programmer's Assistant: Conversational Interaction with A Large Language Model for Software Development," published in the International Conference on Intelligent User Interfaces, Proceedings IUI [20], drew attention due to the number of citations it received in the fields of LLM and software engineering.

### D. The Most Productive Countries and International Cooperation

The research articles were created by authors from 40 different countries (Fig. 3). The top five most productive countries in terms of number of publications were China (n = 29), the United States (n = 28), Germany (n = 16), Canada (n = 11), and Brazil (n = 6). The top five nations by number of citations were Canada (n = 74), the United States (n = 70), Germany (n = 57), China (n = 14), and Finland (n = 14). Consistent with our findings, other studies have identified China and the United States as significant countries in LLM research in different disciplines [23]–[25]. These countries' position as pioneers in LLM and software engineering research reflects their significant investments in these fields.

The review of international collaborations demonstrated that the country that collaborated most was China (Fig. 4). China collaborated with Australia (n = 3), Finland (n = 2), Germany (n = 2), and the United Kingdom (n = 2). Furthermore, there were collaborations between Germany and Finland (n = 2), Germany and the United Kingdom (n = 2), the United States and China (n = 2), the United States and the United Kingdom (n = 2), Australia and Finland (n = 1), and Australia and Singapore (n = 1). In the future, increased international collaboration and generative AI applications like ChatGPT may allow for the development of creative and comprehensive methodologies in software engineering. In addition, guidelines and policies for artificial intelligence and software engineering can be produced in collaboration with other countries.

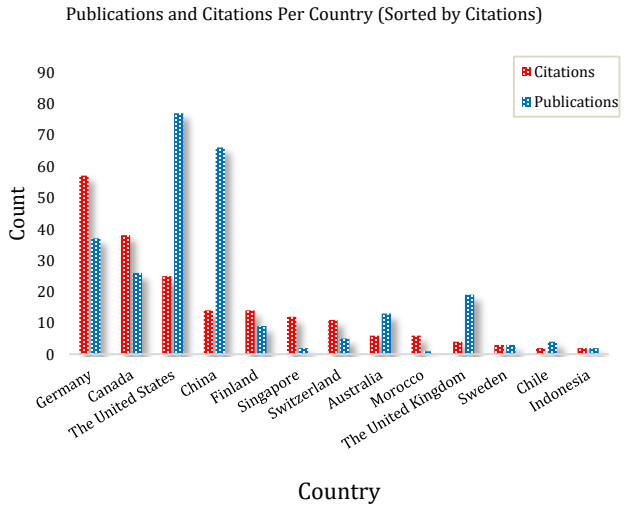


Fig. 3. The Number of publications and citations by country. Note. Countries with at least two publications are presented.

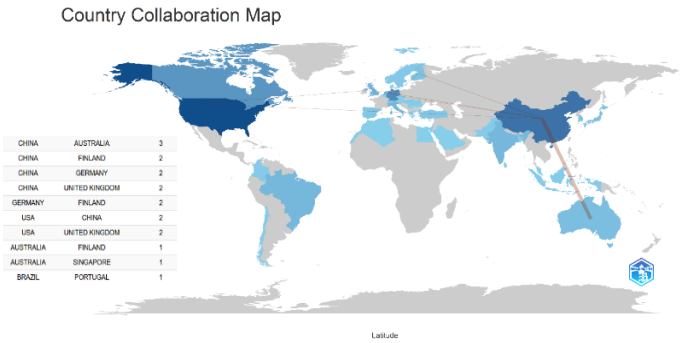


Fig. 4. Country collaboration map. Note. Dark blue indicates more frequent international cooperation. The thickness of the red line between the two countries shows the extent of cooperation.

### E. Co-Occurrence Keyword Analysis

This study identified 1804 keywords (Table III). The following keywords appear at least ten times: software design (n = 158), code (symbols) (n = 68), code generation (n = 40), software testing (n = 34), learning system (n = 32), and artificial intelligence (n = 25). According to Ozkan et al. (Ozkan et al., 2024) and Mesa Fernández et al. (2022), the most commonly used words in software engineering are "software design," "code (symbols)," and "code generation." The frequent use of these words indicates that LLM-based technologies are becoming more popular in the software engineering, especially in code development.

Fig. 5 and Table III shows a visualization of the co-occurrence analysis using the VOS viewer. In the green cluster, the keywords "software design" (TLS = 277) and "code generation" (TLS = 105) are prominent. The emphasis is on the impact and prospective applications of LLM in software engineering. The red cluster contains the keywords "artificial intelligence" (TLS = 62), "generative AI" (TLS = 52), "engineering education" (TLS = 72), "students" (TLS = 82), and "software engineering education" (TLS = 54). In this cluster, the focus is on using LLM in software engineering education. In the yellow cluster, the keywords are "engineering task" (TLS = 45), "prompt engineering" (TLS = 35), "life cycle" (TLS = 39), "modeling languages" (TLS = 31), and "requirement engineering" (TLS = 19) and it is emphasized that the practical application of LLM on software life-cycle development are an essential research area. In the blue cluster, the focus is on the impact of LLM on automation software development tasks, whereas in the purple cluster, the focus is on using LLM in "code (symbols)" (TLS = 153), "quality control" (TLS = 46), "task analysis" (TLS = 37), A"code review" (TLS = 24), and "code quality" (TLS = 20). This analysis visualizes how the interaction between the software engineering field and AI intersects with different aspects and how these terms are positioned together in academic literature.

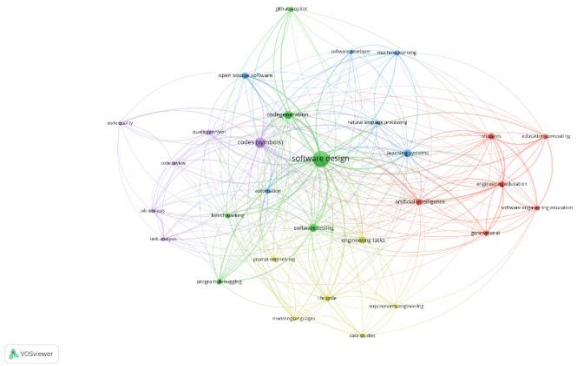


Fig. 5. Visualization of keywords. Note. The analysis is set to the minimum number of keyword occurrences (minimum 10). The network consists of 30 items, 5 clusters, 269 links, and 875 total link strengths.

TABLE III. CO-OCCURRENCE ANALYSIS

| Cluster no. and color | Cluster theme | The number of items | Code (Keywords) | Explanation |
|---|---|---|---|---|
| 1 Red | Software Engineering Education | 6 | Artificial Intelligence, Education Computing, Engineering Education, Generative AI, Software Engineering Education, Students | Researchers delve into educational aspects related to LLM and software engineering. |
| 2 Green | Software Development Tools and Practices | 6 | Benchmarking, Code Generation, GitHub Copilot, Program Debugging, Software Design, Software Testing | Researchers explore topics like the application of LLM in practical software development scenarios. |
| 3 Blue | Automation Software Development Task | 6 | Automation, Learning System Machine Learning, Natural Language Processing, Open-Source Software, Software Developer | The emphasis of ChatGPT's impact on automation, software development task |
| 4 Yellow | Practical Application of LLM in Software Engineering | 6 | Case Studies, Engineering Tasks, Life Cycle, Modeling Languages, Prompt Engineering, Requirements Engineering | The cluster deals with various aspects of software engineering, from requirements engineering and software modeling to security checks. |
| 5 Purple | Quality Control | 6 | Code (symbols), Code Quality, Code Review, Coding Standards, Job Analysis, Quality Control, Task Analysis | The cluster revolves around the various aspects of quality control and evaluation tasks within the software engineering domain. |

Note. The network has 30 items, 5 clusters, 269 links, and a TLS value 875. *Index keywords used by the paper.

### F. Content Analysis

Content analysis can assist prospective academics in identifying essential knowledge gaps in the literature [18]. During the content analysis, five key themes emerged.

Theme 1: Integration of LLM into Software Engineering Education

The first theme focuses on the discussions regarding the use of LLM in educational aspect of software engineering [15], [21], [34], [26]–[33].

Subtheme 1: Potential and threats of LLM in software engineering education.

Using LLMs like ChatGPT in software engineering education has generated debate, highlighting threats and opportunities. The integration of ChatGPT into software engineering education can provide various benefits. ChatGPT can give personalized feedback and enhance individualized student learning experiences [21].

It has advantages, such as how ChatGPT can change how software engineering is taught, making it more practical and relevant to real-life scenarios. Students use ChatGPT to do practical software engineering tasks like collecting user stories, creating use case and class diagrams, and formulating sequence diagrams, which helps them understand real-world applications of their learning [30]. It also has advantages such as Automated Programming Assessment Systems (APASs) as AI-tutors [27] and can aid educators in developing curriculum and preparing course material [29]. Additionally, it can be used in real-time problem solving, collaboration and peer learning, virtual mentoring, generating creative and novel ideas, and research and exploring [15].

Despite the potential benefits, integrating LLMs, such as ChatGPT, into software engineering education raises several concerns and possible limitations. An empirical study with 182 participants in a first-year programming course found no significant difference in performance between students using ChatGPT and those not using it, suggesting that ChatGPT can be safely integrated into education with proper measures [34]. Recent studies in LLMs, including ChatGPT and Copilot, have led to their integration into software development education. An experiment with 32 participants examined LLM use and its correlation with student performance, revealing a negative impact on grades when overused for essential tasks, emphasizing the need for balanced integration of LLM tools in education [31]. Petrovska et al. [32] focused on creatively developing assessments that encourage learners to critically evaluate ChatGPT's output, helping them understand the subject material without the risk of the AI tools "doing the homework." Additionally, Brennan and Lesage [33] evaluated the OpenAI Codex code completion in industry 4.0-oriented engineering programs. They reported that while Codex assisted with simple code completions, students still needed a solid understanding of software development principles, underscoring the importance of foundational knowledge even when using these advanced AI tools.

Overall, integrating LLMs like ChatGPT in software engineering education offers significant advantages, including personalized learning, practical application of concepts, and support for curriculum development. However, it also presents challenges, such as potential negative impacts on student performance if overused and the necessity for students to have solid foundational knowledge despite AI assistance. Students ' critical evaluation of AI-generated content is essential to ensure they truly understand the material. Balancing the use of these tools with traditional learning methods is crucial for maximizing their benefits in educational settings.

Subtheme 2: Future Directions and Adaptation of LLM in Education.

The roadmap for integrating LLMs into software engineering education includes adapting curricula to provide AI literacy, ensuring academic integrity, and reducing academic misconduct. This highlights the necessity for ongoing policy adaptation to technological advancements, marking a critical step toward responsibly integrating ChatGPT in education. Future directions for integrating ChatGPT and similar LLM tools in software engineering education include creating interactive and immersive learning platforms, adopting holistic educational approaches, and continuously evaluating the impact of these tools to optimize their integration and maximize educational benefits [15], [28]–[30].

In summary, integrating ChatGPT into software engineering education requires adapting curricula to include AI literacy, maintaining academic integrity, and preventing misconduct through evolving policies. Future directions involve creating interactive learning platforms, adopting holistic educational approaches, and continuously evaluating the impact of these tools to ensure they provide maximum educational benefits. These steps are essential for responsibly incorporating ChatGPT and similar technologies into education.

Theme 2: Software Development Tools and Practices

This theme delves into the utilization of LLMs for developing and maintaining software quality through advanced code generation and software testing practices. It highlights the potential and limitations of LLMs application in software engineering.

Subtheme 1: Code generation performance and evaluation

Researchers from multiple countries have examined the performance of code generated by LLM. Wang and Chen (Wang & Chen, 2023) noted that LLM-powered code generation has sparked considerable academic interest. An empirical study by Z. Liu et al. [42] assessed ChatGPT's code generation capabilities across five programming languages, focusing on correctness, complexity, and security. Their findings revealed that ChatGPT effectively generates accurate code for issues predating 2021 but encounters difficulties with more recent problems. Similarly, M. Liu et al. [43] conducted a case study using GPT-4 to generate safety critical software code. They explored various methods, including overall requirements, specific requirements, and augmented prompts, concluding that GPT-4 can autonomously generate safety-critical software code suitable for practical engineering applications.

Despite the promising results of LLM's performance in code generation, there is still a debate about their reliability, necessitating more study on evaluation studies [44]. Rodriguez-Cardenas et al. [45], examined LLM-generated code in different scenarios, emphasizing the need for comprehensive evaluation metrics to accurately measure the effectiveness of LLMs in producing reliable and functional code. Preliminary studies have been conducted to this end. Yeo et al. [46], introduced a framework for evaluating LLM-generated code using a metric based on test case pass rates. Similarly, Aillon et al. [47], suggested several metrics for assessing LLM-generated code, including code quality, solution quality, response time, and comparisons with human-generated code.

Other studies have identified significant issues in evaluating LLM-generated code. Mastropaolo et al. [48], assessed the robustness of code generated by GitHub Copilot, highlighting inconsistencies in Copilot's performance. They found that different but similar prompts often resulted in varied outputs, undermining code quality. Zhong and Wang [49] also evaluated the robustness and reliability of LLM-generated code, reporting several limitations. For example, 62% of the code generated by GPT-4 misused APIs, potentially leading to resource leaks, crashes, or unpredictable behavior.

Furthermore, while the generated code can run, it is not always reliable or robust enough for real-world applications. Tests often focus on small or straightforward tasks, which do not reflect the complexity of real-world software development challenges [50]. In addition, Mbaka [51] investigated ChatGPT's effectiveness in validating security threats. The study found that ChatGPT is unreliable in distinguishing real threats from fake ones.

In summary, while LLMs like ChatGPT show potential in code generation, significant issues related to reliability and robustness remain. Comprehensive evaluation metrics and further studies are needed to improve the effectiveness of LLMs in practical software development scenarios.

Subtheme 2: Software testing

This cluster examines the application of LLM in software testing, exploring their potential to innovate and enhance traditional testing methodologies. The research encompasses various aspects of software testing, from unit test generation to exploratory testing, highlighting the transformative potential of LLMs in improving these processes.

Tsigkanos et al. [52] explored the use of LLMs for metamorphic testing in addressing oracle problems within scientific software testing. Scientific software typically handles vast data sets, making manual extraction of essential variables for testing challenging. They developed a method using LLMs to extract these variables from user manuals automatically and compared the LLM-extracted variables with those identified by human experts, finding the LLM method effective. However, despite automating metamorphic testing and reducing human intervention, the approach may still face challenges in managing the vast and varied input-output spaces characteristic of scientific software. Schafer et al. [53] reported the effectiveness of using LLMs to create unit tests, introducing a tool called Test Pilot that generates diverse tests without needing extra training, outperforming existing methods. However, while the tool works well with certain LLMs and specific prompt information, it may not handle more complex or unusual cases in software testing effectively. Thus, further work is needed to enhance the tool's reliability and versatility across different testing scenarios. Tang et al. (Tang et al., 2024) systematically compared unit test suites generated by ChatGPT and EvoSuite, focusing on key factors such as correctness, readability, code coverage, and bug detection capability. Their findings indicate that ChatGPT is a promising tool for generating unit tests in software engineering. Yet, they also identify significant limitations, including reliance on a single LLM model, issues with generalization, and the necessity for ongoing research to improve the reliability and effectiveness of LLM-generated test cases.

Additionally, El Haji et al. [54], assessed GitHub Copilot's ability to generate unit tests automatically. Their experimental study revealed that while GitHub Copilot shows potential, a significant portion of its generated tests fail or are not helpful, particularly without an existing test framework. They concluded that including comments in the code could improve the tool's performance, suggesting that clear documentation might enhance results. This study highlights limitations related to high failure rates, usability issues, dependence on existing test suites, and the proprietary nature of the tool. Similarly, Mehmood et al. [55], compared GitHub Copilot-generated test cases with test cases created by humans, finding that while Copilot shows promise, it has limitations, such as restrictions on the range of scenarios for testing and potential prompt biases. Further research is necessary to understand its capabilities and best uses fully. Despite promising to generate test cases comparable to those created manually, Copilot has limitations in scope, reliance on the prompt quality, range of generated test cases, and the need for more extensive research across a broader range of software development tasks.

Moreover, Copche et al. [56] developed a chatbot called BotExpTest to assist human testers during exploratory testing. This study suggests that integrating chatbots into testing can improve bug detection efficiency and effectiveness. However, further research with larger and more varied sample sizes, extended testing durations, and comparisons across different testing environments and types is needed to understand its capabilities and limitations fully. Finally, LLMs have been utilized for bug detection and fixing [57]–[59]. A significant challenge with LLMs is the need for additional steps to make their output more helpful. After generating results, extra time is required to fix mistakes and provide more detailed instructions, which can be time-consuming. LLMs also struggle to fully understand the context of the code they are testing without clear explanations, leading to missed details and bugs.

In summary, LLMs have shown great potential in various aspects of software testing, including automatic test generation, exploratory testing, and bug detection. While these tools can significantly enhance testing processes, they often require additional steps to fix errors and provide detailed prompts, which can be time-consuming. LLMs struggle with understanding code context without clear descriptions, leading to missed details and bugs. LLM-generated tests have high failure rates and usability issues, especially without existing frameworks or clear documentation. Additionally, LLMs may not handle complex or unusual cases well and are limited by prompt biases and testing scenario restrictions. Despite their potential, LLMs need further refinement and research to improve their reliability and effectiveness in practical software engineering tasks.

Theme 3: Automation Software Development Task

This theme focuses on the integration of LLM in automating software engineering tasks. The key findings highlight significant advancements in this area, emphasizing the transformative impact of LLM automation on traditional software engineering processes.

Rathnayake et al. [60], explores automated technical interviews using advanced chatbot technologies. In the realm of software engineering, automating technical interviews facilitates the assessment of candidates' technical competencies during recruitment. However, challenges remain, such as accurately evaluating technical skills, potential biases in assessing candidate psychology, and ensuring all system components function cohesively. Therefore, further work is needed to enhance the reliability and effectiveness of these automated interview systems. Chen et al. [61] propose an LLM approach for converting written problem descriptions in natural language into domain models, which is typically time-consuming and requires significant expertise. Their findings indicate that while LLMs promise to automate domain modeling, they often miss essential details and do not always follow best practices. Consequently, additional research is necessary to make these tools practical and reliable for everyday use in software engineering. Martins et al. [62], apply LLMs to automatically analyze code, demonstrating their practical application in maintaining high coding standards and improving overall software maintainability. However, the effectiveness of LLMs heavily depends on the quality of input data and the implementation process. Asare et al. [63] examine the security implications of code generated by GitHub Copilot. They conclude that although Copilot performs differently across various vulnerability types, it is not worse than human developers at introducing vulnerabilities. Nonetheless, the study identifies limitations in creating secure code, with Copilot sometimes repeating old coding mistakes, thereby making software vulnerable to attacks. Specifically, Copilot suggests code with the same security flaws about 33% of the time. Its performance varies depending on the type of vulnerability, and it tends to struggle more with older issues. Thus, while Copilot can be helpful, it is not always reliable for generating safe code, necessitating careful instructions from developers to avoid security issues.

Additionally, Wuisang [64] evaluate the effectiveness of ChatGPT for automated bug fixing in Python. Their study highlights ChatGPT's potential as an effective tool for improving code quality and reducing the need for human intervention in bug fixes. They tested 40 different bugs, finding that ChatGPT could correctly fix 30 of them. Although this demonstrates ChatGPT's capability, the failure to fix 10 bugs indicates room for improvement. Despite outperforming other tools like standard bug-fixing methods and Codex, further enhancements are required to ensure reliability in fixing all bugs.

In summary, the research underscores the transformative potential of LLMs in automating various software engineering tasks, including technical interviews, domain modeling, code analysis, and bug fixing. However, challenges remain regarding the reliability and effectiveness of LLMs in these applications. Further refinement and research are essential to fully realizing their potential in practical software development tasks.

Theme 4: Practical Application of LLM in Software Engineering.

Subtheme 1: LLM in Requirements Engineering.

Research in this cluster focuses on integrating LLM in requirements engineering. Jain et al. [65] present a novel approach for summarizing requirements from obligations in software engineering contracts using LLM. This method leverages prompt engineering principles to guide GPT-3 in generating training and ground truth summaries, which are then used to train Natural Language Generation (NLG) models for contract text summarization. Despite its promise, the method heavily relies on the effectiveness of prompt engineering and the performance of NLG models. Consequently, there is a risk that essential details might be missed or not accurately captured, making LLM-generated summaries potentially unreliable. Therefore, analysts must review the original contracts carefully to ensure accuracy.

Spoletini and Ferrari [66] explore integrating automatic formal requirements engineering techniques with LLMs to enhance code generation reliability. These techniques are typically employed in developing complex systems to ensure adherence to specific standards. By combining formal methods with LLM models, the researchers aim to improve the accuracy and reliability of LLM-generated code. However, a significant challenge lies in ensuring that the code generated by LLMs consistently meets these high standards.

Subtheme 2: LLM in Software Modeling and Design.

This theme explores the application of LLMs in software modeling and Unified Modeling Language (UML). Ren et al. [67] investigate the role of chatbots in UML modeling, concluding that while chatbots are valuable for building class diagrams and lay a foundation for further research on their applicability in software engineering diagramming, they are not yet fully capable of capturing all necessary details. This indicates a need for further development and research to enhance their completeness and effectiveness in diagramming tasks. Camara et al. [68] highlight LLMs' practical applications and educational benefits, noting their use in enterprise and software modeling processes. However, they emphasize that educators must rethink how they design and administer assessments, as integrating LLMs requires significant adjustments. Chen and Zacharias (Chen & Zacharias, 2024) propose using generative AI to develop software design principles that assist software developers. Their research identifies fundamental issues with generative AI in software development, including usability problems, data privacy concerns, hallucinations, and a lack of transparency. De Vito et al. [69] introduce ECHO, a novel approach to enhancing the quality of UML use cases using LLMs. ECHO employs a co-prompt engineering technique and an interactive process with the LLM to improve use cases based on practitioner feedback. Despite its potential, ECHO faces challenges such as the need for substantial effort to develop effective prompts and ensure iterative improvements. Additionally, their experiment showed that while ECHO could improve use case quality, further refinement, and validation are necessary to ensure consistent and reliable outcomes across diverse scenarios.

Melo [70] proposes the design of context-based adaptive interactions between software developers and chatbots to foster solutions and knowledge support. Although the proposed method shows potential, it remains difficult for chatbots to

understand and adapt to the specific contexts of software development. The study highlights the need for more research to understand developers' expectations and improve the interaction between developers and chatbots. Finally, Petrovic [71] examines the integration of ChatGPT into software development practices, focusing on automated security checks and real-time feedback to enhance software security and reliability during the design phase. However, the study identifies challenges, such as the need to refine and process automated results from ChatGPT to be useful for developers and system administrators. Additionally, the evaluation was limited to specific tools, which may affect the generalizability of the findings to other tools or environments.

In summary, the research highlights that LLMs can significantly enhance various aspects of software engineering, from requirements engineering and software modeling to security checks. They provide practical tools for improving quality in software development processes. However, specialized models and further research are necessary to fully realize the potential of LLMs in practical applications and address existing limitations.

Theme 5: Quality Control

This theme delves into utilizing LLMs for quality control and evaluation tasks within the software engineering domain. Lu et al. [72] introduce Llama-reviewer, a model designed to automate code reviews in software development. The model is noted for its efficiency, using fewer resources than traditional models, and the findings indicate promising results even with less training. However, the study acknowledges that the limited training epochs might restrict the model's capability to manage more complex or diverse code review tasks. Ronanki et al. (Ronanki et al., 2024) investigate the application of ChatGPT for evaluating the quality of user stories in Agile software development. The results show that ChatGPT's assessments align well with human evaluations, but the study highlights the challenge of ensuring the trustworthiness of ChatGPT's outputs. Tufano et al. [73] compare a deep learning model and ChatGPT in mimicking developers' tasks during code reviews, such as adding comments on code changes or fixing code based on comments. They found that ChatGPT struggled to comment on code as effectively as human reviewers. This research underscores the need for more specialized studies to enhance code review automation, as general models like ChatGPT cannot fully replicate human reviewers' capabilities, especially in tasks like code review.

Furthermore, Pantelimon and Posedaru [74] explore how ChatGPT can generate code snippets, templates, and functions from natural language input, aiding in bridging the gap between technical and non-technical team members in software development. While this tool helps developers quickly find and fix bugs, enhancing the accuracy of automated code review and testing, concerns about potential over-reliance on ChatGPT and the limitations of its ability to comprehend intricate technical concepts are noted. In addition, Martins et al. [62] present an automated GitHub bot using LLMs to enforce SOLID principles during code reviews. This bot provides immediate feedback, improving code quality, particularly for new programmers, and integrates seamlessly into GitHub. However, they also state that the tool faces many challenges in handling various code review scenarios.

In summary, while these studies illustrate the potential of LLMs in software engineering, they also highlight the need for further research to address limitations related to model robustness, handling complex tasks, reducing biases, and improving integration and usability in real-world software development environments. Future work should focus on developing more specialized LLM models tailored to specific tasks like code reviews, enhancing the robustness and adaptability of these models through more extensive and varied datasets, and refining approaches like co-prompt engineering for better accuracy. Additionally, efforts should be made to mitigate over-reliance on automation, reduce biases in training data, and improve the interaction between developers and LLM tools. Expanding testing in diverse environments, integrating advanced LLM models, and developing comprehensive training for non-experts to use these AI tools effectively are crucial steps for future research.

## V. Discussion

The current study acknowledges several limitations inherent in the bibliometric analysis approach. First, while Scopus and Web of Science are extensive databases, they may not encompass all relevant publications on the subject. Consequently, future studies should incorporate additional databases such as Google Scholar and PubMed to ensure a more comprehensive analysis. Second, although VOS Viewer and Bibliometrix software are reliable tools for bibliometric analysis, other software options such as SciMat, Sci2, Bibexcel, Gephi, Cite Space, Pajek, and UCINET should also be utilized in future research to enhance robustness and validity.

Furthermore, the number of studies comparing different versions of ChatGPT, specifically versions 3.5, 4.0, and 4o in the context of software engineering, remains limited. Future research should explore the impact of these versions on outcomes and consider comparisons with other LLM tools such as Google Gemini, LLAMA, Microsoft Copilot, and Claude. Additionally, it is essential to examine the effects of various AI technologies, including DALL-E, DeepL, Typecast AI, and Resemble AI, on software engineering processes and outcomes.

## VI. Conclusion

To our knowledge, this is the first bibliometric analysis study on using LLMs in software engineering. This study identifies the nations, authors, and publications that have contributed significantly to the field. The content analysis results show that the publications are organized around three key themes: 1) integration of LLMs into software engineering education, 2) application of LLMs in software engineering, and 3) potential and limitations of LLMs in software engineering. Our investigation reveals that China and the United States have the most publications, but international collaboration is limited. Consequently, future studies should encourage scholars to interact with researchers from other nations.

There is a gap in the literature concerning studies that explore LLMs and specific software engineering topics, which

future studies should address. Firstly, integrating LLMs like ChatGPT into software engineering education offers significant benefits, including personalized learning, practical application of concepts, and support for curriculum development. However, challenges such as potential negative impacts on student performance if overused and the necessity for students to have solid foundational knowledge despite AI assistance must be addressed. Students must evaluate AI-generated content critically to ensure genuine understanding. Therefore, balancing these tools with traditional learning methods is essential for maximizing their benefits in educational settings. To effectively integrate LLMs, curricula must be adapted to include AI literacy, maintain academic integrity, and prevent misconduct through evolving policies. Future directions involve creating interactive learning platforms, adopting holistic educational approaches, and continuously evaluating the impact of these tools to ensure they provide maximum educational benefits. Secondly, although LLMs like ChatGPT show promise in code generation, significant reliability and robustness issues remain. Comprehensive evaluation metrics and further studies are needed to assess and improve the effectiveness of LLMs in practical software development scenarios. ChatGPT has demonstrated great potential in software testing in areas such as automatic test generation, exploratory testing, and bug detection. However, these tools also have limitations and require further research to optimize their application in software engineering. Thirdly, research under the theme of automation in software engineering highlights the transformative potential of LLMs in automating various tasks, from technical interviews to domain modeling, code analysis, and bug fixing. Despite these advancements, challenges remain regarding the reliability of LLMs in these automated tasks.

## VII. Future Work

Furthermore, LLMs can significantly enhance various aspects of software engineering, including requirements engineering, software modeling, and security checks. They provide practical tools for improving quality in software development processes. Nevertheless, there is a need for specialized models and further research to fully realize the potential of LLMs in practical applications and address existing limitations. Finally, studies demonstrate the potential of LLMs in software engineering but also underscore the need for further research to address limitations related to model robustness, handling complex tasks, reducing biases, and improving integration and usability in real-world software development environments. Future work should focus on developing more specialized LLM models tailored to specific tasks like code reviews, enhancing the robustness and adaptability of these models through extensive and varied datasets, and refining approaches like co-prompt engineering for better accuracy. Additionally, efforts should be made to mitigate over-reliance on automation, reduce biases in training data, and improve interactions between developers and LLM tools. Expanding testing in diverse environments, integrating advanced LLM models, and developing comprehensive training for non-experts to use these tools effectively are crucial steps for future research.

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## APPENDIX

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# HSI Fusion Method Based on TV-CNMF and SCT-NMF Under the Background of Artificial Intelligence

Dapeng Zhao[1], Yapeng Zhao[2], Xuexia Dou[3]*
Henan Polytechnic, Zhengzhou 450000, China[1, 3]
Henan Polytechnic University, Jiaozuo 454150, China[2]

***Abstract*—The fusion of hyper-spectral images has important application value in fields such as remote sensing, environmental monitoring, and agricultural analysis. To improve the quality of reconstructed images, an HSI fusion method based on fully variational coupled non-negative matrix factorization and sparse constrained tensor factorization techniques is proposed. Spectral sparsity description is enhanced through sparse regularization, image spatial characteristics are captured using differential operators, and convergence is improved by combining proximal optimization with augmented Lagrangian methods. The experiment outcomes on the AVIRIS and HYDICE datasets indicate that the proposed method achieves peak signal-to-noise ratios of 38.12 dB and 37.56 dB, respectively, and reduces spectral angle errors to 3.98° and 4.12°, respectively, significantly better than the other two comparative methods. The contribution of each module is further verified through ablation experiments. The complete algorithm performs the best in all indicators, verifying the synergistic effect of sparse regularization, total variation regularization, and coupled factorization strategies. In HSI fusion tasks under various complex lighting and noise conditions, the performance of the proposed algorithm is particularly excellent, fully demonstrating its robustness and applicability in complex scenes. The method proposed by the research effectively improves the fusion quality of HSI, providing an efficient and robust solution for the analysis and application of HSI.**

***Keywords*—HSI; NMF; sparse regularization; SCT; augmented Lagrangian method***

## I. Introduction

Hyper-spectral images (HSI) have continuous spectral bands and HSI resolution, providing powerful information support for land classification, target recognition, environmental monitoring, and other fields [1]. For example, HSI can be used to finely distinguish vegetation types, monitor water pollution, detect mineral distribution, and identify target materials, all of which are difficult to achieve with traditional optical images [2]. However, existing HSI devices are limited by optical and sensor technologies, making it difficult to simultaneously capture both HSI and high spatial resolution images [3]. This constraint renders the acquisition of HSI that boasts both high spectral and spatial resolution a significant technical hurdle—one that remains incompletely overcome. To address this issue, the fusion technology of HSI and multi-spectral images (MSI) has emerged, with the goal of combining the advantages of both to generate fused images with HSI and high spatial resolution. By combining the advantages of HSI and MSI, fusion technology can generate fused images that retain both spectral details of HSI and spatial clarity of MSI, thus breaking through the hardware limitations of a single device. Traditional methods often struggle to achieve a balance between spectral fidelity and spatial resolution. Therefore, an HSI fusion method combining non-negative matrix factorization (NMF) and tensor factorization techniques has been proposed in this study. NMF can effectively extract hidden features from data while maintaining the non- negativity of the data, which enables it to better preserve spectral information when processing HSI. Secondly, tensor factorization can capture multidimensional interactions in HSI data and uncover deep information. In addition, the study enhances image spatial smoothness by introducing total variation (TV) regularization and optimizes spectral characteristics using sparsity constraint (SC), which can effectively preserve spectral and spatial information while reducing noise interference. Finally, the use of proximal alternating optimization (PAO) and augmented Lagrangian methods significantly improves the convergence speed and computational efficiency of the model. Therefore, the proposed method is suitable for solving the problem of HSI fusion, which can effectively improve the fusion quality of HSI and provide an efficient and robust solution for the analysis and application of HSI.

The first section of the study furnishes an exhaustive account of the specific principles and implementation of the proposed HSI fusion method. The second section presents the experimental setup, performance evaluation indicators, and comparative experimental results on different datasets, and analyzes the ablation experiment to verify the effectiveness of each module in the method. Finally, the third section summarizes the main achievements of the research and explores the potential applications and future development directions of the method.

## II. Related Work

In recent times, artificial intelligence learning technology has made significant progress in the field of HSI integration. Dian et al. proposed a zero sample learning technique to improve the clarity of HSI and accurately measure the spectral and spatial characteristics of imaging sensors. This technology also achieved dimensionality reduction of HSI data, optimized model size and storage requirements, while maintaining fusion accuracy. Experiments showed that this method exhibited significant performance in both efficiency and accuracy [4]. Wu

et al. proposed a deep interpretable network that effectively integrates HSI and MSI through advanced coupling matrix factorization constraints. This network alternately processed HSI and MSI data through two branch subnets, predicting abundance and membership matrices respectively. The experimental results showed that this method was superior to existing model driven and data-driven fusion techniques in visual analysis and quality assessment [5]. Although this method could capture complex nonlinear relationships, it performed poorly in preserving spectral information, especially under high noise conditions. Zhao et al. raised an HSI classification method based on local feature decoupling and hybrid attention module. This method utilized gradient oriented histogram algorithm to preprocess HSI data, achieving preliminary nonlinear decoupling. Experimental results demonstrated that, compared to other transformer-based and traditional HSI classification methods, the proposed approach exhibited superior classification performance. [6]. Yang et al. combined tensor theory with deep learning and proposed a new unsupervised deep tensor network for the fusion of HSI and MSI. They designed a tensor filtering layer and constructed a coupled tensor filtering module based on it. This module worked in conjunction with the projection module to jointly train HSI and MSI in an unsupervised end-to-end manner. The effectiveness of this method was verified through experiments on simulated and actual remote sensing datasets [7]. However, when dealing with ultra-high resolution HSI, the demand for computing resources significantly increased, making it difficult to meet the requirements of real-time processing.

NMF is a commonly-used matrix factorization approach in signal processing, image processing, text mining, and other fields. It can effectively extract hidden features from data while maintaining its non-negativity [8]. Sun et al. proposed an adaptive graph regularized NMF model with global constraints for data representation. This model utilized the self- representation characteristics of data to construct an adaptive graph, in order to more accurately capture the relationships between samples, and used graph factorization techniques to simplify the model and enhance its discriminative power. Finally, the effectiveness of the model was validated on multiple databases through experiments [9]. However, using fixed regularization parameters was difficult to adapt to changes in different input conditions, such as lighting variations, noise levels, etc., resulting in limited generalization ability in practical applications. Yu et al. proposed a robust asymmetric NMF clustering method for directed networks. This method took into account the non-Gaussian nature of real-world network errors and assumed that the errors follow a heavier tail Cauchy distribution. The experiment outcomes showed that this method performed better than traditional NMF and other clustering methods in both real and artificial networks [10]. Yuan et al. raised a new model for embedding multi-view attribute networks with integrated manifold regularization. This model captured the Riemannian geometry structure of the network by introducing manifold regularization, which compensated for the shortcomings of traditional NMF in information capture. Non-negative coefficient matrices were obtained using NMF, and the amount of information embedded in the network was enhanced by combining cooperative regularization and manifold regularization. Through experimental verification on multiple real datasets, the model performed better than current advanced algorithms in node classification tasks [11].

In summary, existing HSI fusion is difficult to achieve a good balance between spectral fidelity and spatial resolution. Moreover, deep learning methods have a strong dependence on large-scale annotated data and high computational complexity, which affects their practicality. Based on this, an innovative HSI fusion method combining NMF and tensor factorization was proposed. By introducing to TV regularization to enhance the spatial smoothness of images and using SC to optimize spectral characteristics, both spectral and spatial information are effectively preserved while reducing noise interference. In addition, the use of PAO and augmented Lagrangian methods significantly improves the convergence speed and computational efficiency of the model. The research aims to achieve high spectral resolution while providing high spatial resolution and image quality.

## III. Methods and Materials

### A. HSI Mixed Pixel Factorization Technology Based on Linear Spectral Mixing Model

The core concept of NMF is to factorize the image data collected by sensors into two nonnegative matrices, enabling the identification of endmember spectra and estimation of corresponding abundances without assuming pure pixels. Coupled NMF (CNMF) is a classic technique for HSI fusion. During the fusion process, CNMF alternately processes spectral images, extracting endmember matrices and abundance matrices until the algorithm converges [12]. Finally, these two matrices are multiplied to obtain high-resolution HSI, and the fusion process is shown in Fig. 1 [13].

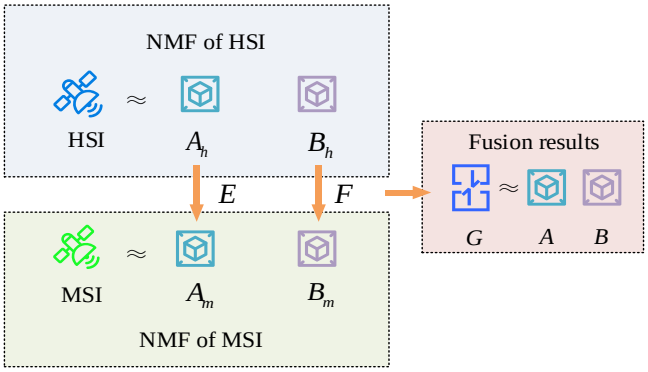



Fig. 1. CNMF fusion process.

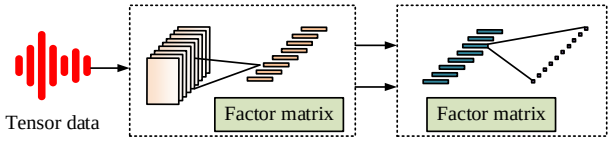
In Fig. 1, the HSI is factorized into a base matrix $A_h$ and a coefficient matrix $B_h$. The factorization of MSI involves breaking it down into a base matrix $A_m$ and a coefficient matrix $B_m$. By using the correlation matrices $E$ and $F$, joint constraints between the two data sources are enforced, and the fusion result $G$ is obtained as the product of the base matrix $A$ and the coefficient matrix $B$, completing the spectral image fusion process. The cost function of the CNMF algorithm is shown in Eq. (1) [14].

$$CNMF(A,B)=\left\|X-A_hB_h\right\|^2+\left\|Y-A_mB_m\right\|^2 \quad (1)$$

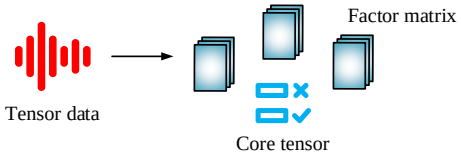
In (1), $X$ and $Y$ respectively represent the input HSI and MSI. $B_h$ and $A_m$ represent the abundance matrix of spatial downsampling and the endmember matrix of spectral downsampling, respectively, as expressed in Eq. (2).

$$\begin{cases} B_h = BF \\ A_m = EA \end{cases} \quad (2)$$

In Eq. (2), non-negative tensor factorization (NTF) is an extension of NMF that factorizes high-dimensional tensor data. It is specially designed for factorizing and modeling high-dimensional tensor data. Tensors can be seen as high-dimensional forms of matrices, widely used to describe multidimensional data structures such as three-dimensional image sequences, video data, and complex relationships in sensor networks. Unlike traditional matrices, tensors can preserve the multidimensional structural characteristics of data, making them more suitable for analyzing and modeling data with high-dimensional interaction relationships. Two commonly-used tensor factorization models are shown in Fig. 2 [15].




(a) CP decomposition diagram




(b) Tucker decomposition diagram

Fig. 2. Tensor factorization model.

Fig. 2 (a) and (b) show typical CANDECOMP/PARAFAC (CP) factorization and Tucker factorization, respectively. CP factorization factorizes a tensor into a linear combination of rank one tensors, each consisting of the outer product of three vectors. Tucker factorization, on the other hand, represents a tensor as the product of a core tensor and multiple factor matrices. The core tensor is used to capture the global relationships of the tensor, while the factor matrix is used to represent the feature information in each dimension. These two factorization methods are used for feature extraction and pattern recognition in multidimensional data analysis. The mathematical expression for CP factorization is shown in Eq. (3) [16].

$$y=\sum_{r=1}^{R}\omega_r(a_r\cdot b_r\cdot c_r) \quad (3)$$

In Eq. (3), $y$ represents the target tensor, $R$ is the rank of the factorization, $\omega_r$ is the weight coefficient of the $r$ th rank component, $(a_r\cdot b_r\cdot c_r)$ represents the $r$ th rank tensor, which is a tensor generated by the outer product of three vectors. The mathematical expression for Tucker factorization is shown in Eq. (4).

$$y=\Phi_1C_2D_2H \quad (4)$$

In Eq. (4), $\Phi$ represents the core tensor and $C,D,H$ represents the factor matrix. Further extension of Tucker factorization leads to block term factorization (BTD), as shown in Fig. 3 [17]

In Fig. 3, each part is generated by modular multiplication of a kernel tensor and three factor matrices. The factorization result can be seen as representing the tensor as a combination of multiple low rank tensor blocks, with the core tensor describing the relationships within the blocks and the factor matrix describing the characteristics of the tensor in various dimensions. This factorization method is used to represent complex tensor structures more finely and is suitable for handling multi-modal or multidimensional data.

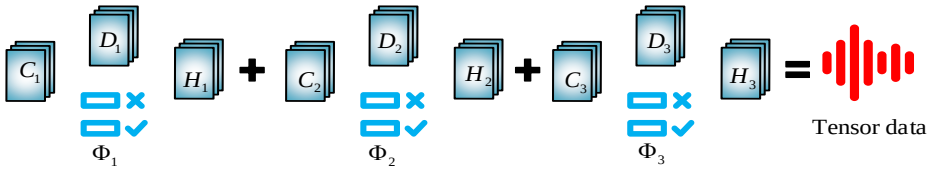



Fig. 3. BTD structure.

### B. HSI Fusion Algorithm Based on TV-CNMF and SCT-NMF

To further enhance the effectiveness of HSI fusion, a mixed pixel factorization technique combining linear spectral mixing model is studied, and tensor factorization method is adopted to propose an HSI fusion algorithm based on TV-CNMF and sparse constrained tensor (SCT) -NMF to enhance image detail preservation and denoising effects. Tensor factorization is a method of multi-linear algebra, which is a high-dimensional extension of matrix factorization and can effectively handle three-dimensional and above data structures, such as video and audio. It can capture multidimensional interactions in data and uncover deep information, which is difficult to achieve through matrix factorization. Based on the CNMF model, this study enhances the sparsity description of HSI through sparse regularization of shortest endmember distance and abundance, and captures the segmentation smoothness of the image using differential operators to reduce the impact of noise on the fusion effect. A TV-CNMF HSI fusion algorithm, TV-CNMF, is proposed. The objective function of the algorithm is shown in Eq. (5) [18].

$$\frac{1}{2}\min_{A,B} CNMF(A,B)+\lambda_1\left\|AP\right\|_F^2+\lambda_2\left\|B\right\|_1+\lambda_3\left\|D_xB\right\|_1+\lambda_3\left\|D_yB\right\|_1 \quad (5)$$

In (5), $\lambda_1$, $\lambda_2$ and $\lambda_3$ both represent regularization parameters, where $\lambda_1$ controls the strength of TV regularization and is used to enhance the spatial smoothness of the image. $\lambda_2$ controls the intensity of sparse constraints to optimize spectral sparsity. $\lambda_3$ regulates the coupling relationship between HSI and MSI to balance the information from both data sources. To determine the optimal values of these hyper-parameters, a grid search method is employed in the study. The value range of $\lambda_1$ is [0.1, 1, 10], the value range of $\lambda_2$ is [0.01, 0.1, 1], and the value range of $\lambda_3$ is [0.001, 0.01, 0.1]. Through grid search, the impact of different parameter combinations on model performance is systematically evaluated, and the optimal parameter combination ($\lambda_1$=1, $\lambda_2$ =0.1, $\lambda_3$=0.01) is selected. However, this function involves constrained optimization, and the model contains numerous unknowns, making it quite difficult to solve directly. Therefore, it is necessary to transform Eq. (5) into an unconstrained optimization function and introduce auxiliary variables as constraint terms, as shown in Eq. (6).

$$\frac{1}{2}\|X-AB_h\|+\frac{1}{2}\|Y-A_mB\|+\lambda_1\|AP\|_F^2+\lambda_2\|B\|_1+\lambda_3\|D_xB\|_1 +\lambda_3\|D_yB\|_1+l_{R^+}(A)+l_{R^+}(B) \quad (6)$$

In Eq. (6), $l_{R^+}(A)$ represents $A\geq 0$, $l_{R^+}(B)$ represents $B\geq 0$. After normalizing the objective function, $A$ and $B_h$ are optimized respectively, and the updated formula for $B_h$ is obtained as shown in Eq. (7).

$$B_h \leftarrow B_h \frac{A^TX}{A^TAB_h} \quad (7)$$

In Eq. (7), $\leftarrow$ represents the update rule. For the optimization problem of $A$, an auxiliary variable is first introduced, and the resulting sub-problem is shown in Eq. (8).

$$\arg\min_A \frac{1}{2}\|X-AB_h\|_F^2+\lambda_1\|AP\|_F^2+l_{R^+}(I_1) \quad (8)$$

In Eq. (8), $I_1$ represents the auxiliary variable. Eq. (8) is derived to obtain the augmented Lagrangian function as shown in Eq. (9).

$$L(I_1,A,Z_1)=\frac{1}{2}\|X-AB_h\|_F^2+\lambda_1\|AP\|_F^2+l_{R^+}(I_1)+\frac{\vartheta_1}{2}\|A-I_1-Z_1\|_F^2 \quad (9)$$

In Eq. (9), $Z_1$ represents the Lagrange multiplier and $\vartheta_1$ represents the penalty parameter. Using the augmented Lagrangian alternative direction method of multipliers (ADMM) for solving, the result is shown in Eq. (10).

$$\begin{cases} A^{k+1}=\arg\min_A(A,I_1^k,Z_1^k) \\ I_1^{k+1}=\arg\min_{I_1}(A^{k+1},I_1,Z_1^k) \\ Z_1^{k+1}=\arg\min_{Z_1}(A^{k+1},I_1^{k+1},Z_1) \end{cases} \quad (10)$$

In Eq. (10), $k$ is the number of iterations. Similarly, the solution process of $B_h$ is shown in Fig. 4.

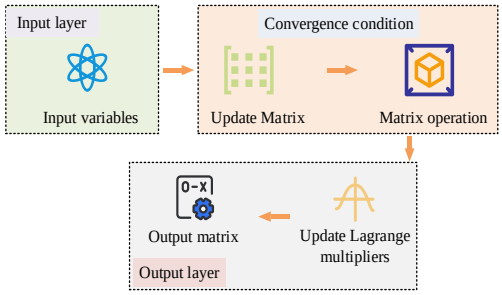



Fig. 4. The process of ADMM solving $B_h$.

In Fig. 4, one variable is optimized at a time while the other variables are kept constant. By iterating through this loop, each variable is continuously optimized, and the optimal value of the objective function is ultimately approached. The final TV-CNMF algorithm flow is shown in Fig. 5.

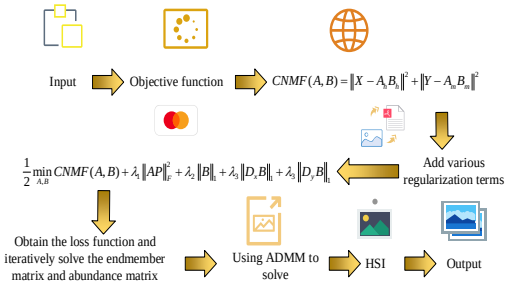



Fig. 5. TV-CNMF algorithm process.

In Fig. 5, the input includes HSI with low spatial resolution and MSI with high spatial resolution, and the error function is minimized using the CNMF model. Among them, regularization terms are introduced to optimize the sparsity and smoothness of matrices $A$ and $B$. By alternately optimizing the loss function, the fused high-resolution HSI is finally obtained, and the ADMM algorithm is used to complete the optimization solution. When processing HSI fusion, although matrix factorization algorithm achieves good results, it may damage the spatial structure and spectral correlation of HSI, and fail to fully utilize all structural information of the images. The third-order tensor factorization is more suitable for HSI, reducing information loss, but there are shortcomings in preserving details. To this end, an SC-based image fusion algorithm called SCT-NMF is proposed, which combines NTF and NMF to effectively protect data structure information, explore spatial details, and enhance solution stability. Firstly, the BTD and NMF models are

combined, and the sparsity of semi norm constrained abundance is introduced to construct an efficient fusion model, as represented in Eq. (11).

$$\min_{C,D,H,V} \frac{1}{2}\left\|\chi_H - \sum_{r=1}^{R} P_1 C_r (P_2 D_r)^T o_r\right\|^2 + \frac{1}{2}\left\|\chi_M - \sum_{r=1}^{R} C_r D_r^T (P_3 o_r)\right\|_F^2 \quad (11)$$

In Eq. (11), $\chi_H$ and $\chi_M$ respectively represent the image data of HSI and MSI, $V$ represents the sparse coding matrix, $o_r$ is the endmember vector, and $P$ represents the projection matrix. Due to the fact that the fusion model is a non-convex optimization problem, it is necessary to fix one variable while keeping the other variables constant during solving, so that the optimization problem for each fixed variable is convex. Therefore, the PAO method can be used to solve the variables $C, D, H$ in the model, and the outcomes are represented in Eq. (12).

$$\begin{cases} C = \arg\min_{C} g(C,D,H) + \mu\left\|C - C^{pre}\right\|_F^2 \\ D = \arg\min_{D} g(C,D,H) + \mu\left\|D - D^{pre}\right\|_F^2 \\ H = \arg\min_{H} g(C,D,H) + \mu\left\|H - H^{pre}\right\|_F^2 \end{cases} \quad 12)$$

In Eq. (12), $\mu$ is a penalty parameter used to control the difference between the current iteration value and the previous iteration value. $\mu_1$ is used to control the difference between the newly obtained $C$ and the $C^{pre}$ obtained in the previous iteration. $\mu_2$ is used to control the difference between the newly obtained $D$ and the $D^{pre}$ obtained in the previous iteration. $\mu_3$ is used to control the difference between the newly obtained $H$ and the $H^{pre}$ obtained in the previous iteration. $g(C,D,H)$ is the objective function, representing the coupling relationship of $C, D, H$. $C^{pre}$, $D^{pre}$, and $H^{pre}$ represent the values of the previous iteration of $C, D, H$. The SCT-NMF algorithm flow is shown in Fig. 6.

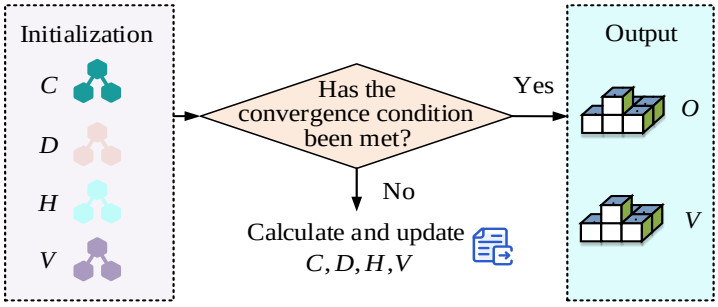



Fig. 6. SCT-NMF algorithm process.

In Fig. 6, the SCT-NMF algorithm initializes the factor matrix $C, D, H$ and iteratively updates each matrix to minimize the objective function. The core idea of this algorithm is to use sparse regularization and tensor factorization techniques, combined with constraint conditions, to optimize the objective function until the convergence conditions are met. Finally, the algorithm outputs a sparse matrix $O$ and a sparse encoding matrix $V$, representing the feature representation and sparsity encoding of the data, respectively. Finally, by introducing the sparse encoding matrix of SCT-NMF into the objective function of TV-CNMF, both spatial details and SCs can be optimized simultaneously. Combining TV regularization with sparse encoding matrix can make the image fusion process more robust, reduce the influence of noise, and improve the effect of detail preservation. In the fused image results, TV-CNMF can provide strong denoising and smoothing effects, while SCT-NMF can better protect the structural information and details of the image. In order to evaluate the computational efficiency of TV-CNMF and SCT-NMF algorithms, the complexity of TV-CNMF and SCT-NMF is analyzed using Big-O representation. Assuming the size of the input HSI image is $M \cdot N \cdot L$, where $M$ and $N$ are spatial dimensions, $L$ is spectral dimension, and $r$ is the factorized rank. The main computational cost of TV-CNMF comes from the optimization of matrix factorization and regularization terms. The time complexity of matrix factorization is $O(MNr)$, and the time complexity of TV regularization is $O(MrN)$. Therefore, the overall time complexity of TV-CNMF is $O(MNr + MrN + MN) \cdot k$. The main computational overhead of SCT-NMF comes from tensor factorization and optimization of sparse constraints. The time complexity of tensor factorization is $O(MNrL)$, and the time complexity of sparse constraints is $O(MN)$. Therefore, the overall time complexity of SCT-NMF is $O(MNrL \cdot k + MN)$.

## IV. Results

### A. Performance Testing of HSI Fusion Algorithm Based on TV-CNMF and SCT-NMF

To confirm the performance of the raised fusion algorithm, it was tested against the Residual Selective Kernel Attention-based U-net (RSKAU-net) [19] and the Efficient Phase-induced Gabor Cube Selection and Weighted Fusion (EPCS-WF) method [20]. Two datasets, AVIRIS and HYDICE, were selected, and Peak Signal-to-Noise Ratio (PSNR), Spectral Angle Mapper (SAM), and Root Mean Square Error (RMSE) were used as indicators. The outcomes are in Table I.

According to the data in Table I, the proposed algorithm achieved a PSNR of 38.12 dB on the AVIRIS dataset, outperforming RSKAU-net (35.42 dB) and EPCS-WF (36.78 dB) by 7.6%, indicating superior image reconstruction quality. SAM was 3.98°, which was 25.5% lower than RSKAU net and exhibited stronger spectral fidelity; and the RMSE was 0.031, lower than other algorithms, indicating the minimum reconstruction error. On the HYDICE dataset, the proposed algorithm achieved a PSNR of 37.56 dB, 7.7% higher than RSKAU-net. In addition, the SAM of the algorithm proposed in the research was 4.12°, which was 27.3% lower than RSKAU net. The RMSE was 0.033, which also outperformed other algorithms. Overall, the algorithm proposed in the research performed the best in terms of PSNR, SAM, and RMSE. It outperformed RSKAU net and EPCS-WF in terms of spectral fidelity, spatial resolution, and pixel-level error in reconstructed images, demonstrating excellent spectral and spatial property preservation capabilities. It was suitable for HSI fusion and analysis tasks. The loss function changes of the three algorithms on different datasets are shown in Fig. 7.

TABLE I Performance Test Results of Fusion Algorithm

| Database | Algorithm | PSNR | SAM | RMSE |
|---|---|---|---|---|
| AVIRIS | RSKAU-net | 35.42 | 5.34 | 0.042 |
| | EPCS-WF | 36.78 | 4.56 | 0.038 |
| | Ours | 38.12 | 3.98 | 0.031 |
| HYDICE | RSKAU-net | 34.87 | 5.67 | 0.045 |
| | EPCS-WF | 35.91 | 4.89 | 0.041 |
| | Ours | 37.56 | 4.12 | 0.033 |

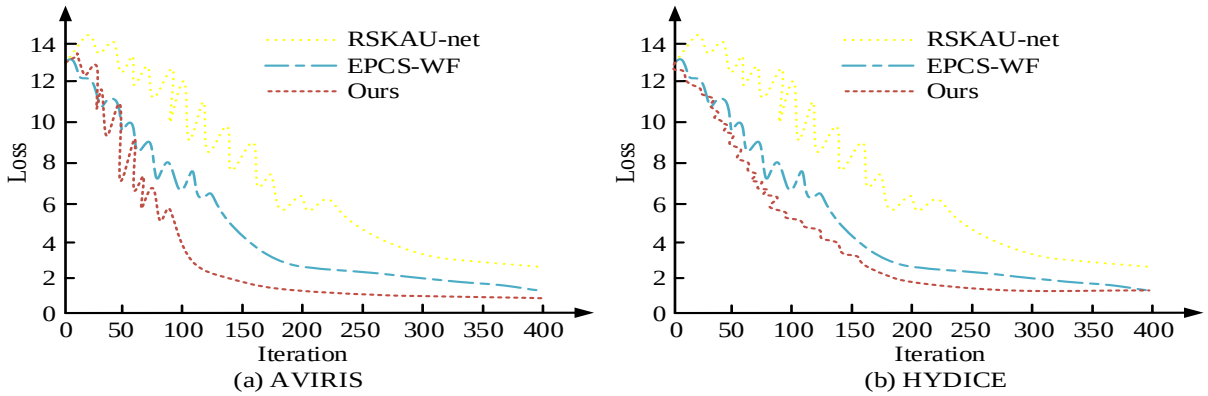



Fig. 7. Changes in loss function on different datasets.

Fig. 7(a) and Fig. 7(b) respectively show the trend of the loss function of three algorithms with iteration times on the AVIRIS and HYDICE datasets. Overall, the loss value gradually decreased as the number of iterations increased, and each algorithm eventually tended to converge. On the AVIRIS dataset, the initial loss of RSKAU net was relatively high, the decrease was slow, and the final loss value was significantly higher than other algorithms. The descent rate of EPCS-WF was slightly faster, but the final loss was still higher than the algorithm proposed by the research. The loss value of the algorithm proposed by the research decreased the fastest and was significantly better than other algorithms at the 100th iteration, resulting in the lowest loss value in the end. On the HYDICE dataset, both RSKAU net and EPCS-WF converged slowly, and the final loss value was higher than the algorithm proposed in the study. The algorithm proposed by the research not only had the fastest convergence speed and the best optimization performance on two datasets, but also had the lowest final loss value, indicating that its fusion performance and optimization effect were better than other algorithms. Meanwhile, it had good robustness and universality, and was suitable for HSI fusion tasks. Through ablation experiments, the specific contributions of each module to the algorithm's performance were gradually verified. Firstly, the complete algorithm consisted of multiple key components, including CNMF, sparse regularization TV, and ADMM. In ablation settings, the complete model was considered the baseline model, which included all modules. The algorithm that removed sparse regularization and only retained coupling tensor factorization and TV regularization was referred to as A1. The algorithm that removed TV regularization and only retained sparse regularization and coupling tensor factorization was referred to as A2. The algorithm that removed coupling factorization and replaced it with independent NMF was referred to as A3. The algorithm that removed all regularization terms and only used coupling factorization was referred to as A4. The algorithm that replaced the optimization strategy with a simple multiplication update method was referred to as A5. The ablation experiment results in the two datasets are shown in Table II, using PSNR, SAM, and RMSE as evaluation indicators.

TABLE II RESULTS OF ABLATION EXPERIMENT

| Database | Algorithm | PSNR (dB) | SAM (°) | RMSE |
|---|---|---|---|---|
| AVIRIS | A1 | 38.12 | 3.98 | 0.031 |
| | A2 | 36.45 | 4.76 | 0.038 |
| | A3 | 36.23 | 4.91 | 0.042 |
| | A4 | 35.15 | 5.45 | 0.048 |
| | A5 | 34.52 | 5.72 | 0.052 |
| HYDICE | A1 | 37.56 | 4.12 | 0.033 |
| | A2 | 35.98 | 4.78 | 0.041 |
| | A3 | 35.62 | 4.96 | 0.045 |
| | A4 | 34.88 | 5.67 | 0.052 |
| | A5 | 34.15 | 5.94 | 0.054 |

According to Table II, in the AVIRIS dataset, A1 had the best PSNR, SAM, and RMSE of 38.12dB, 3.98°, and 0.031, respectively. The PSNR of A2 and A3 decreased to 36.45dB and 36.23dB respectively, SAM increased to 4.76° and 4.91°, and RMSE increased to 0.038 and 0.042, indicating that sparse regularization and TV regularization played an important role in spectral fidelity and reconstruction quality. The PSNR of A4 decreased to 35.15dB, SAM increased to 5.45°, and RMSE reached 0.048. The PSNR of A5 further decreased to 34.52dB, SAM increased to 5.72°. RMSE was 0.052, indicating that the lack of regularization and coupling factorization significantly reduced model performance. In the HYDICE dataset, A1 had the best PSNR, SAM, and RMSE of 37.56dB, 4.12°, and 0.033, respectively. The PSNR of A2 and A3 decreased to 35.98dB and 35.62dB, respectively, while SAM increased to 4.78° and 4.96°, and RMSE increased to 0.041 and 0.045. The PSNR of A4 was 34.88dB, SAM was 5.67°, and RMSE was 0.052. Finally, in A5, PSNR decreased to 34.15dB, SAM increased to 5.94°, and RMSE was 0.054. Overall, A1 performed the best on both datasets, validating the effectiveness and importance of sparse regularization, TV regularization, and coupled factorization. The algorithm A5, which removed all regularization terms, performed the worst, further demonstrating the importance of regularization for model optimization and robustness.

### *B. Analysis of the Effect of HSI Fusion Algorithm based on TV-CNMF and SCT-NMF*

To verify the application effect of the proposed algorithm, simulation experiments were conducted to compare and analyze the applicability of the algorithm under different lighting conditions and noise levels. Selecting SAM, Spectral Correlation Coefficient (SCC), and Spectral Mean Square Error (SMSE) as indicators, the results are shown in Table III.

In Table III, under illumination conditions, the SAM of the proposed algorithm in high light environments was 3.89°, significantly better than RSKAU net and EPCS-WF. SCC was 0.965, significantly higher than RSKAU net and EPCS-WF, while SMSE was the lowest, only 0.031, indicating that it could better preserve spectral information under high light conditions and had high spectral fidelity and low error. Under low light conditions, the SAM of the proposed algorithm was 4.32°, SCC was 0.952, and SMSE was 0.036, which were also superior to RSKAU net and EPCS-WF, demonstrating good spectral fidelity and robustness. At the noise level, the SAM of the proposed algorithm in high noise environments was 4.89°, and the SCC was 0.941, both significantly better than RSKAU net and EPCS-WF. The SMSE was the lowest, at 0.038, demonstrating strong noise resistance. Under low noise conditions, the proposed algorithm had a SAM of 5.02°, SCC of 0.952, and SMSE of 0.041, which were also superior to the other two compared algorithms and maintained advantages in spectral fidelity and error control.

TABLE III APPLICABILITY UNDER DIFFERENT LIGHTING CONDITIONS AND NOISE LEVELS

| Condition | Algorithm | SAM (°) | SCC | SMSE |
|---|---|---|---|---|
| High light | RSKAU-net | 5.34 | 0.912 | 0.042 |
| | EPCS-WF | 4.56 | 0.932 | 0.038 |
| | Ours | 3.89 | 0.965 | 0.031 |
| Low light | RSKAU-net | 6.21 | 0.892 | 0.051 |
| | EPCS-WF | 5.02 | 0.915 | 0.045 |
| | Ours | 4.32 | 0.952 | 0.036 |
| High noise | RSKAU-net | 6.78 | 0.876 | 0.056 |
| | EPCS-WF | 5.89 | 0.903 | 0.048 |
| | Ours | 4.89 | 0.941 | 0.038 |
| Low noise | RSKAU-net | 7.12 | 0.896 | 0.058 |
| | EPCS-WF | 6.21 | 0.912 | 0.041 |
| | Ours | 5.02 | 0.952 | 0.063 |

In Fig. 8(a) and Fig. 8(b) respectively show the CPU usage comparison of three methods under different lighting and noise conditions. In Fig. 8(a), under high light conditions, the RSKAU net method had the highest CPU utilization rate of 56.6%. The EPCS-WF method was 52.2%. The lowest calculation efficiency of the method proposed by the research was 50.6%, indicating that it had the highest computational efficiency. Under low light conditions, the CPU utilization rates of RSKAU net and EPCS-WF methods were 51.1% and 45.2%, respectively, while the proposed method remained the lowest at 45.5%, demonstrating good computational efficiency and stability. In Fig. 8(b), under high noise conditions, the EPCS-WF method had the highest CPU utilization rate of 60.5%. The RSKAU net method was 51.7%. The method proposed by the research was 53.3%, demonstrating higher resource utilization efficiency. Under low noise conditions, the CPU utilization rates of RSKAU net and EPCS-WF methods were 46.6% and 56.3%, respectively, while the proposed method was 59.8%, still performing well in terms of computational performance and resource utilization. The Salinas dataset and Chikusei dataset were selected for the study, with 100 randomly selected samples each, to evaluate the running time of the three algorithms in HSI fusion tasks. The results are shown in Fig. 9.

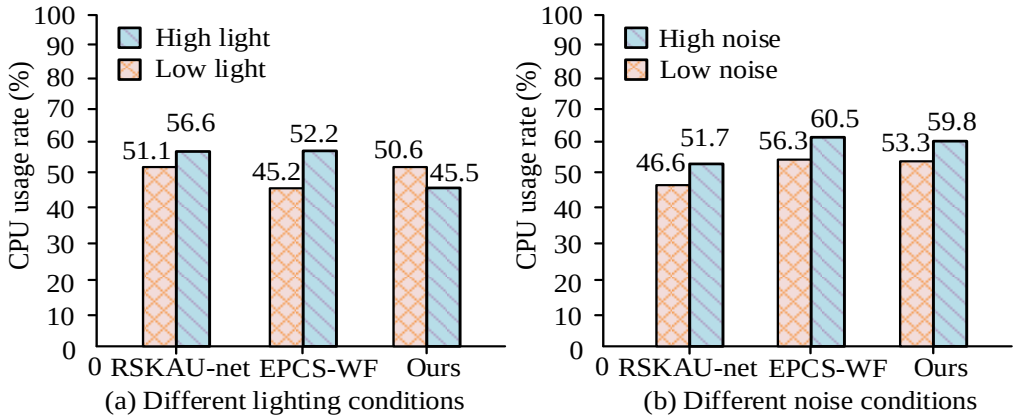



Fig. 8. Comparison of CPU usage under different lighting and noise conditions.

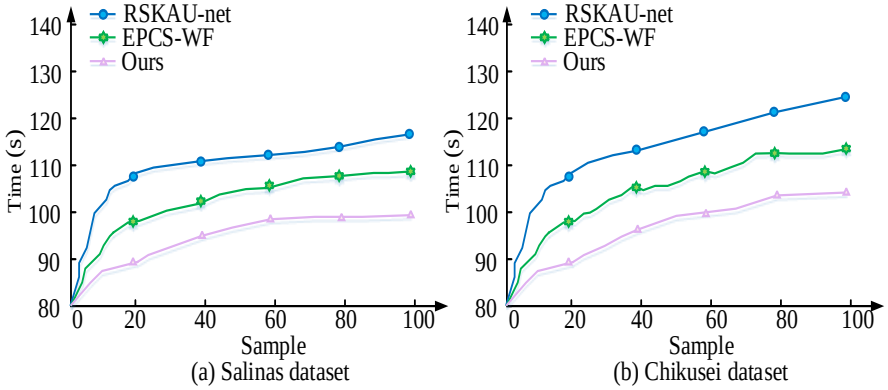



Fig. 9. Comparison of running time under different sample sizes.

Fig. 9(a) and Fig. 9(b) show the trend of running time for different algorithms on different datasets, respectively. In Fig. 9(a), the running time of the proposed method was consistently lower than that of RSKAU net and EPCS-WF, indicating better computational efficiency. Although the running time of EPCS-WF was relatively low, as the sample size increased, the running time gradually increased, and the gap between the proposed method and the research gradually widened. The running time of RSKAU net was the highest, and the growth trend was the most significant, indicating that its computational cost was relatively high when processing large-scale samples. In Fig. 9(b), the proposed method also showed the lowest running time, and the growth trend was relatively flat, indicating that the proposed method not only had advantages in computational efficiency, but also had good adaptability and stability on different datasets. The performance of EPCS-WF on this dataset was also relatively close to the proposed method, but still slightly higher. The running time of RSKAU net increased the fastest with an increase in sample size, further confirming its shortcomings in computational efficiency. Based on the results of the two datasets, the proposed method outperformed the other two methods in terms of running time, indicating that it could not only provide high-quality fusion results but also achieve them at a lower computational cost when processing HSI fusion tasks. This is particularly important for practical applications where computing resources are limited. The qualitative visual comparison results of the three methods in different scenarios are shown in Fig. 10.

From Figs 10(a) to 10(d) show the original images of four scene images and the fusion results of three methods, respectively. As shown in the figure, in the sky scene, the proposed method could better capture the color gradient of the sky at sunset while maintaining the delicate texture of the clouds, while other methods may result in unnatural color transitions or loss of texture details. Under the EPCS-WF method, there were phenomena of exposure and distortion in the image. In the farmland scene, the method proposed by the research not only clearly displayed the outline of the farmland, but also preserved rich details of the soil and vegetation. In contrast, RSKAU net was not accurate enough in color reproduction, while EPCS-WF lacked detailed representation. For architectural scenes, both RSKAU net and the methods proposed by the research could display the subtle textures of windows and walls while maintaining the clarity of the building structure, while EPCS-WF still needed to improve the richness of details. Finally, in the street scene, the proposed method could better restore the true colors of the street and trees, while maintaining high contrast and clarity of the image, resulting in a good display of the texture of the street and the details of the trees. However, color distortion occurred in the fused images of RSKAU net, while EPCS-WF lacked attention to detail. Overall, the method proposed in the study could effectively preserve the spectral and spatial information of HSI during fusion, while reducing noise interference and improving image quality.

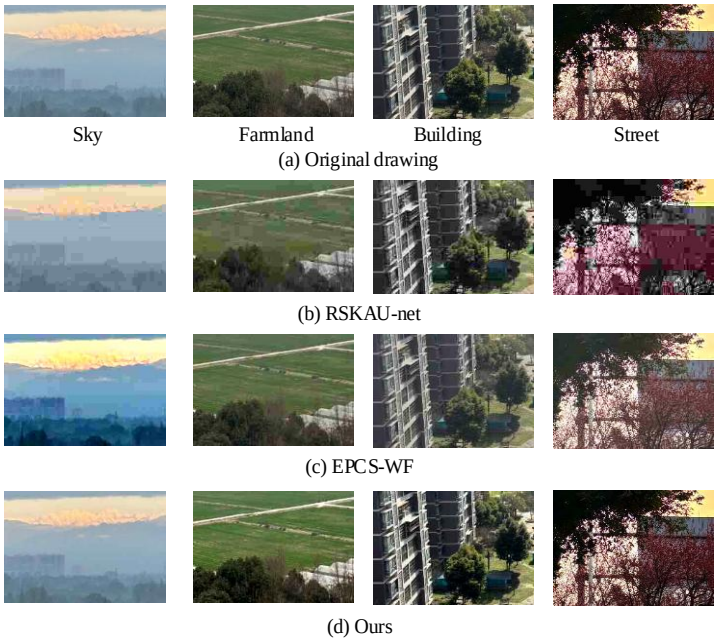



Fig. 10. Qualitative visual comparison of images in different scenarios.

## V. Discussion

An HSI fusion algorithm based on TV-CNMF and SCT-NMF was proposed in this study. By combining TV regularization and SCT, the spectral and spatial characteristics were optimized, and the convergence and computational efficiency of the model were improved through efficient optimization strategies. The experimental results on the AVIRIS and HYDICE datasets showed that the proposed method significantly outperformed RSKAU net and EPCS-WF in terms of PSNR, SAM, and RMSE. On the AVIRIS dataset, the PSNR of the proposed method reached 38.12 dB, which was 7.6% higher than RSKAU net, and the SAM decreased to 3.98°, which was 25.5% lower than RSKAU net. On the HYDICE dataset, PSNR reached 37.56 dB, an increase of 7.7% compared to RSKAU net, and SAM decreased to 4.12°, a decrease of 27.3%. In addition, the method proposed in the research performed particularly well under high noise and low light conditions, further verifying its robustness and applicability. Compared with reference [7], although the unsupervised deep tensor network proposed by Yang J et al. performed well in HSI and MSI fusion tasks, its robustness in handling complex lighting and noise conditions still needed to be improved. The method proposed by the research significantly improved robustness under high noise and low light conditions by introducing adaptive regularization strategies and efficient optimization algorithms, while reducing dependence on large-scale annotated data. Through ablation experiments, the key contributions of sparse regularization, TV regularization, and coupled factorization strategies to model performance were identified. The complete model performed the best on all indicators, demonstrating that the synergistic effect of each module significantly improved the fusion quality of images. Compared with existing algorithms, the proposed method not only had significant advantages in spectral fidelity and spatial resolution but also demonstrated lower computational costs and higher practical application potential. The method proposed in the research was suitable for HSI fusion tasks under complex lighting and noise conditions and could significantly improve the fusion quality of images, providing an effective solution for the analysis and application of HSI.

## VI. Conclusion

In summary, an HSI fusion algorithm based on TV-CNMF and SCT-NMF was proposed, which significantly improved the spectral fidelity and spatial resolution of images by combining TV regularization and SCT. The experimental results showed that this method exhibited strong robustness and applicability under complex lighting and noise conditions. In addition, this method had broad practical application potential in fields such as satellite imaging and medical imaging. For example, in satellite imaging, this method could be used to process hyperspectral data in real-time, improving the accuracy of land cover classification and target recognition. In medical imaging, this method could be used for multi-modal image fusion to assist in disease diagnosis and treatment planning. However, there are still some limitations to the research, as the performance of the method may decrease in high noise or high dynamic environments, especially in extreme noise conditions or scenarios where the target is moving rapidly. Although the method proposed by the research improved computational efficiency, the time complexity and computational resource requirements were still high when processing ultra-high resolution HSI, which may limit its real-time performance in practical applications. Future research can further explore deep learning-based enhancement methods, such as designing deep neural network modules to optimize the selection of regularization parameters or enhance feature extraction capabilities, to further improve fusion performance. Meanwhile, adaptive regularization techniques can be studied to dynamically adjust regularization parameters based on the characteristics of input data, to improve the robustness of the algorithm under different lighting, noise, and dynamic conditions. In addition, for

the processing requirements of ultra-high resolution HSI, the time complexity and computational resource utilization of the algorithm can be further optimized, and the possibility of distributed computing or hardware acceleration can be explored.

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# Energy Management Controller for Bi-Directional EV Charging System Using Prioritized Energy Distribution

Ezmin Abdullah[1], Muhammad Wafiy Firdaus Jalil[2], Nabil M. Hidayat[3]*
Wireless High-Speed Network Research Interest Group (RIG), Universiti Teknologi MARA,
40000 Shah Alam, Selangor, Malaysia[1, 2]
Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Malaysia[1, 3]

***Abstract*—The growing adoption of electric vehicles (EVs) has intensified the need for efficient, intelligent, and grid-independent Bi-directional charging systems. Conventional EV charging solutions heavily rely on grid electricity, leading to high energy costs, grid instability, and low renewable energy utilization. Existing Bi-directional charging systems often lack real-time prioritization of energy sources, fail to optimize solar and energy storage system (ESS) usage, and do not incorporate adaptive control mechanisms for varying grid conditions. To address these gaps, this study proposes an Energy Management Controller (EMC) for Bi-Directional EV Charging, integrating a prioritized solar to ESS to grid energy distribution strategy to maximize renewable energy usage while ensuring system stability and cost efficiency. The proposed EMC is implemented on an ESP32 microcontroller and manages energy flow via a 6-channel relay module. A temperature-based safety mechanism is embedded to prevent overheating, shutting down relays if the system temperature exceeds 50°C. The control logic dynamically adjusts power flow based on grid stress levels, solar irradiance, ESS state of charge (SOC), and EV battery SOC. The system is monitored using ThingsBoard for real-time visualization and InfluxDB for historical data analysis. Experimental validation across 12 predefined operational scenarios demonstrated that the EMC effectively reduces grid dependency to 15%, achieves renewable energy utilization of up to 90%, and maintains a fast relay switching response time of 50ms. The safety mechanism successfully prevents overheating, ensuring reliable operation under all test conditions.**

***Keywords*—Energy management controller; Bi-directional EV charging system; safety features; control algorithms; energy flow optimization; EV battery protection; testing and validation; thingsboard platform; InfluxDB database***

## I. INTRODUCTION

Electric vehicles are quickly becoming more common on our roads, and with them comes the need for reliable and efficient charging infrastructure. All chargers in the market use unidirectional chargers with traditional charging methods consisting of constant current (CC) and constant voltage (CV) [1]. In response to this growing demand, a Bi-directional smart controller for EV chargers has been developed, offering an innovative solution to enable the Bi-directional current flow of electricity between the EV charger and the power grid. Compared to traditional fuel vehicles, electric vehicles (EVs) have significant advantages in terms of preserving oil resources and lowering carbon emissions. The usage of electric vehicles (EVs) has increased, and governments and manufacturers throughout the world are noticing [2]. Relays or switches are also used in the DC-DC converter to regulate the voltage and current levels between the main battery and the power system. Relays or switches are used in the three-port converter topology to control the flow of electricity between the main battery, AC grid, and auxiliary power systems. They help ensure that the electricity flows smoothly and efficiently between the different components and that the charging and discharging processes are carried out safely and effectively [3].

V2G is a key component of the smart grid initiative and can be used better to manage the voltage stability of the power system. The penetration of V2G into the power system may introduce a high level of volatility due to precarious charging/discharging operations, hence emphasizing the need for a real-time management option [4], [5]. The paper defines V2G penetration as the percentage of the substation's electric power capacity and investigates the impact of one-phase and three-phase V2G interconnection at given penetration levels on the power system parameters to be monitored (voltage, voltage stability, SVR control, and power/energy loss). The results show improved system performance and economical operation with three-phases and system-wide V2G integration [6]. V2G can also provide ancillary services such as regulation and spinning reserves, which are essential for maintaining grid stability [7], [8].

The concept of this project is to construct an energy management controller using an ESP32-WROOM-32 controller to control the flows of the current for a Bi-directional EV Charging System by controlling the conditions of 6 relays in the Bi-directional EV charging system based on the 4 input conditions of Grid Stress, Solar Irradiance, Energy Storage System (ESS) Soc and EV Soc to determine the 12 possible output scenarios which can be monitored through IoT platform. The project is built using the ESP32 controller, relays, and safety features. The system is programmed by using Arduino IDE, an open-source platform, that provides a vast community of developers and readily available online resources that enable smooth operation and troubleshooting.

To enhance the project's capabilities, an ESP32 Wi-Fi module in the ESP32 controller was incorporated into the system architecture. This addition allows for remote monitoring and

*Corresponding Author.

control via the ThingsBoard platform, facilitating real-time data collection and analysis using InfluxDB Cloud to optimize the system flow.

This work is practically motivated by the urgent need for a cost-efficient and renewable-integrated Bi-directional EV charging infrastructure in developing countries. The proposed Energy Management Controller addresses real-world constraints such as fluctuating solar availability, rising energy costs, and limited grid stability. Therefore, by dynamically prioritizing solar, ESS, and grid inputs to maintain optimal energy flow and operational safety.

The remainder of this paper is organized as follows: Section II reviews related works on Bi-directional charging systems and highlights the research gaps. Section III presents the methodology, system architecture, and prioritized energy distribution algorithm. Section IV discusses implementation, hardware setup, and validation scenarios. It showcases the monitoring and data analysis approach. Section V presents the results and discussion. Finally, Section VI concludes the paper and suggests future enhancements.

## II. Related Work

### A. Literature Review

Several research studies have explored different aspects of Bi-directional EV charging systems, yet significant gaps remain in optimizing energy flow, integrating renewable energy sources, and enhancing system reliability. The study on an Interleaved Bi-Directional AC–DC Converter [9] focuses on enabling Bi-directional power flow between the EV charger and the power grid through control algorithms, yet it lacks considerations for renewable energy integration and grid stress optimization. Similarly, the Cloud-based Smart EV Charging Station Recommender enhances user accessibility through a data-driven selection system [10], but does not address real-time energy management or system reliability. Research on Smart Power Flow Controllers for EVs in Smart Grids improves coordination between EVs and the grid using fuzzy logic control, yet it does not consider dynamic energy distribution strategies incorporating solar and ESS [11]. The Universal Controller for Smart Grids standardizes device applications in distribution networks but does not focus specifically on Bi- directional EV energy management [12].

Other works, such as A PFC Hysteresis Current Controller for Totem-pole Bridgeless Bi-directional EV chargers [13], and the Virtual Synchronous Machine-Based Control of Single- phase Bi-Directional Battery Chargers [14], mainly focus on hardware-level improvements, enhancing power quality and stability but lacking comprehensive energy optimization across multiple sources. Meanwhile, LabVIEW- based Data Management Design for EV Bi- Directional Charger Testing contributes to efficient data storage but does not explore real-time energy balancing and optimization strategies [15]. In the context of EV charging station safety, research on Electrical Safety Considerations in Large-Scale EV Charging Stations identifies potential risks but does not integrate real-time fault detection mechanisms for i- directional charging systems [16]. Lastly, Safety-Integrated Online Deep Reinforcement Learning for Mobile Energy Storage System Scheduling introduces an AI-driven Volt/VAR control strategy, optimizing MESS and PV systems [17], but does not specifically address Bi-directional EV charging scenarios or user energy prioritization.

Overall, these studies highlight the implementation of the Bi- directional Controller by focusing on the current flow controller in the EV charging system. However, there is a limitation found in the previous research such as, a system with renewable energy dependency, possible scenario optimization and flexibility, and fail-safe mechanism. Therefore, the primary goal of this project is to develop Energy Management Controllers for Bi-directional EV Charging systems with solar energy dependency, Bi-directional scenarios, and safety features. This approach enhances the overall efficiency and sustainability of EV charging systems compared to the limitations found in the previous research.

## III. Methodology

### A. System Architecture

Fig. 1 shows the Block Diagram of the Energy Management Controller for a Bi-directional EV Charging system with safety features to control the current flows in the system.

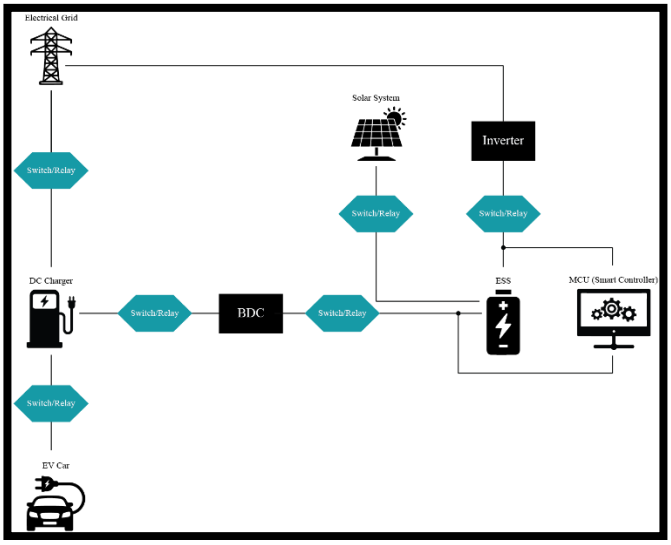


Fig. 1. Block diagram of the energy management controller for Bi-directional EV charging system with safety features.

The system architecture in Fig. 1, shows the connection between all sections that are involved in the Energy Management Controller for Bi-directional EV Charging system with safety features. The main function of the relay in this system is to control the current flows in the Bi-directional EV Charging System. The relay will be controlled by an ESP32 controller to determine which relay will turn ON or OFF based on the 12 scenarios that will be encountered in real time to control the flow of the current in the micro grid. Relay 1 is connected between the Electrical Grid and DC Charger. Relay 2 is connected between the DC Charger and the EV Car. Relay 3 is connected between the DC Charger and the Bi-directional Controller. Relay 4 is connected between a Bi-directional Controller and an Energy Storage System (ESS). Relay 5 is connected between the Energy Storage System (ESS) and the

Solar System. Lastly, Relay 6 is connected to the Energy Storage System (ESS) and the Inverter. These 6 relays will be controlled by the Energy Management Controller for a Bi-directional EV charging system with safety features. Fig. 2, illustrates the block diagram of the input and output of the developing a Bi- directional EV controller.

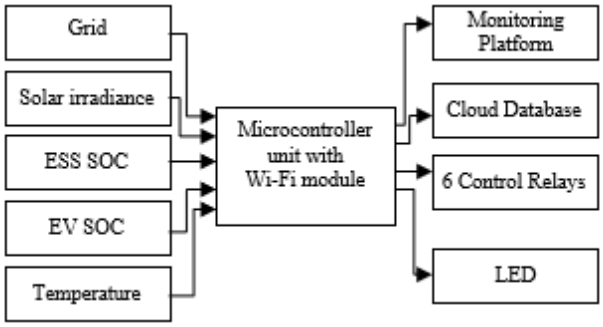


Fig. 2. Block diagram of the energy management controller for Bi-directional EV charging system with safety features.

### *B. Workflow and Prioritize Energy Distribution Algorithm*

The flowchart in Fig. 3, illustrates the decision-making process of an energy management controller with an integrated safety mechanism.

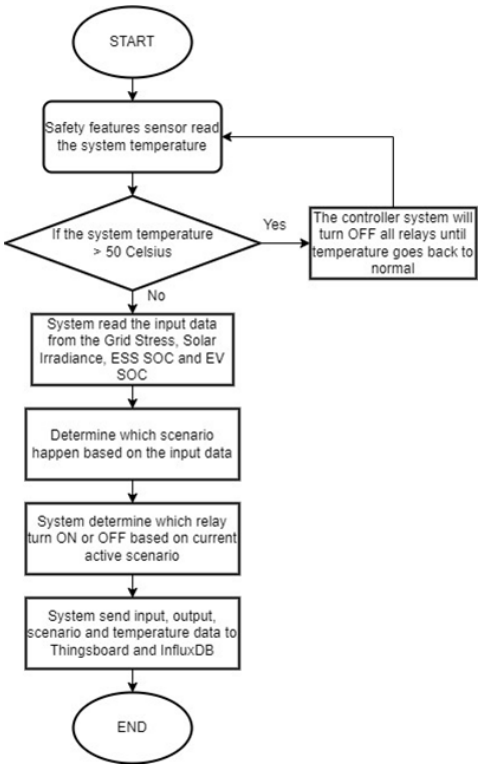


Fig. 3. General flowchart of the system.

The process begins with a safety feature sensor that continuously monitors the system temperature. If the temperature exceeds 50°C, the controller immediately shuts down all relays to prevent overheating and resumes operation only when the temperature returns to a safe level. If the temperature is within the acceptable range, the system collects input data from various sources, including grid stress, solar irradiance, ESS state of charge (SOC), and EV SOC**.** Based on these inputs, the system determines which operational scenario is active and accordingly decides which relays should be turned ON or OFF to optimize energy distribution. Finally, the system transmits real-time data, including input values, output status, active scenario, and temperature readings**,** to ThingsBoard and InfluxDB for monitoring and analysis**,** ensuring efficient and safe operation of the energy management system.

To optimize energy management in a Bi-directional EV charging system, a prioritized energy distribution model is developed, ensuring that energy sources are utilized in the following hierarchical order: Solar > ESS > Grid. The total energy required by the system, denoted as $E_{demand}$, is supplied through a combination of solar energy, $E_{solar}$, energy storage system (ESS), $E_{ESS}$, and grid energy $E_{grid}$, forming the fundamental energy balance equation.

$$E_{demand} = E_{solar} + E_{ESS} + E_{grid} \quad (1)$$

where, each energy source is allocated in order of priority to minimize grid dependency and maximize renewable energy utilization.

The first priority is given to solar energy. If the available solar power is sufficient to meet the demand ($E_{solar} \geq E_{demand}$), then solar is used exclusively and no additional energy is drawn from ESS or the grid.

$$E_{used} = \min(E_{solar}, E_{demand}), \quad E_{grid} = 0,\ E_{ESS} = 0 \quad (2)$$

If solar energy is insufficient to meet demand ($E_{solar} < E_{demand}$), then the ESS is utilized as the secondary energy source, provided its state of charge (SOC) is above the minimum discharge threshold($SOC_{min}$). The ESS contribution is defined as

$$E_{ESS} = \min(E_{demand} - E_{solar}, E_{ESS,max}) \quad (3)$$

Ensuring that ESS discharges only the required energy while maintaining system stability. The energy supplied at this stage is:

$$E_{used} = E_{solar} + E_{ESS} \quad (4)$$

If both solar and ESS are insufficient, the grid acts as the last resort, supplying only the remaining unmet demand.

$$E_{grid} = E_{demand} - (E_{solar} + E_{ESS}) \quad (5)$$

where, $E_{grid} \geq 0$ ensures grid energy is used only necessary. The total energy supplied at this stage becomes.

$$E_{used} = E_{solar} + E_{ESS} + E_{grid} \quad (6)$$

To maintain system reliability and optimize performance, constraints are imposed. The ESS discharge constraint ensures energy is supplied only when the SOC is above a predefined threshold:

$$E_{ESS} = 0, \text{only if } SOC < SOC_{min} \quad (7)$$

where, $SOC_{min}$ = 40% based on battery manufacturer recommendations. If the ESS is above the threshold, the available ESS energy is

$$E_{ESS} = \min(E_{demand} - E_{solar}, E_{ESS,max}) \quad (8)$$

Similarly, grid energy is utilized only if solar and ESS cannot meet demand, ensuring minimal reliance on non-renewable sources:

$$E_{grid} = E_{demand} - (E_{solar} + E_{ESS}), if\ E_{grid} > E_{grid,min} \quad (9)$$

Finally, to ensure system stability, the sum of all available energy sources should never exceed the total demand:

$$E_{solar} + E_{ESS} + E_{grid} = E_{demand} \quad (10)$$

The final model for prioritized energy distribution can be expressed as (11). This model effectively prioritizes renewable energy, enhances energy efficiency, and minimizes grid reliance, ensuring an optimal and sustainable Bi-directional energy management system for EV charging applications.

$$E_{used} = \begin{cases} E_{solar}, & if\ E_{solar} \geq E_{demand} \\ E_{solar} + min(E_{ESS}, E_{demand} - E_{solar}), & if\ E_{ESS} > 0\ and\ E_{solar} < E_{demand} \\ E_{solar} + E_{ESS} + (E_{demand} - E_{solar} - E_{ESS}), & if\ E_{solar} + E_{ESS} < E_{demand} \end{cases} \quad (11)$$

Table I shows the configuration parameters for the prioritized energy distribution control algorithm.

TABLE I. CONFIGURATION PARAMETERS FOR CONTROL ALGORITHM

| Parameter | Description | Value | Justification |
|---|---|---|---|
| ESS Minimum SOC | Minimum SOC threshold to allow ESS discharge | 40% | Battery manufacturer recommendation |
| High Irradiance Threshold | Threshold for sufficient solar irradiance | > 500 W/m² | Empirical solar energy availability |
| High Grid Stress | Grid instability indicator (binary signal) | 1 = High, 0 = Low | Simulated grid state |
| EV SOC Discharge Threshold | EV SOC required to discharge to ESS | > 70% | Prevents deep cycling |
| Temperature Cutoff | Temperature threshold to trigger relay shutdown | 50°C | Safe operation limit for ESP32 and relays |

### C. Schematic Diagram

Fig. 4 and Table II shows the schematic diagram of the hardware components of Energy Management controllers and pseudocodes for Bi-directional EV Charging Systems with Safety Features respectively. When the system starts working, the DHT22 sensor will make sure the system can operate under safe conditions by measuring the Temperature of the ESP32 controller to make sure the temperature is normal under 50° Celsius to allow the system to operate smoothly. If the temperature exceeds 50° Celsius, the system will shut down all 6 relays until the system temperature returns to safe temperature below 50° Celsius. After the system makes sure the temperature is normal to operate using the DHT22 sensor, the system will begin acquiring data from the Grid Stress conditions, Solar Irradiance value, ESS SOC percentage value, and EV SOC percentage value.

TABLE II. PSEUDOCODE FOR THE PROGRAM CODES DEVELOPMENT

**Pseudocodes**

```
Initialize system
Turn off all relays

Loop:
  Read temperature from DHT22 sensor
  If temperature > 50°C:
    Turn off all relays
    Publish "HIGH" to temperature alarm
  Continue loop

Else:
  Publish "LOW" to temperature alarm

  Read input values:
    - GridStress (0 = Low, 1 = High)
    - SolarIrradiance (W/m²)
    - ESS_SOC (%)
    - EV_SOC (%)

  Determine active scenario based on inputs

  If SolarIrradiance > 500 and ESS_SOC < 40% and GridStress = HIGH:
    Activate Relay 6 only (Scenario A)

  Else if GridStress = LOW and SolarIrradiance > 500 and ESS_SOC <
          40% and EV_SOC < 70%:
    Activate Relays 1, 2, 5, and 6 (Scenario B)

  Else if GridStress = LOW and SolarIrradiance > 500 and ESS_SOC <
          40% and EV_SOC > 70%:
    Activate Relays 1, 2, 3, 4, and 5 (Scenario C)

  [Continue for all 12 scenarios…]

  Send data to ThingsBoard (MQTT) and InfluxDB:
    - Input conditions
    - Relay status
    - Active scenario
    - Temperature
```

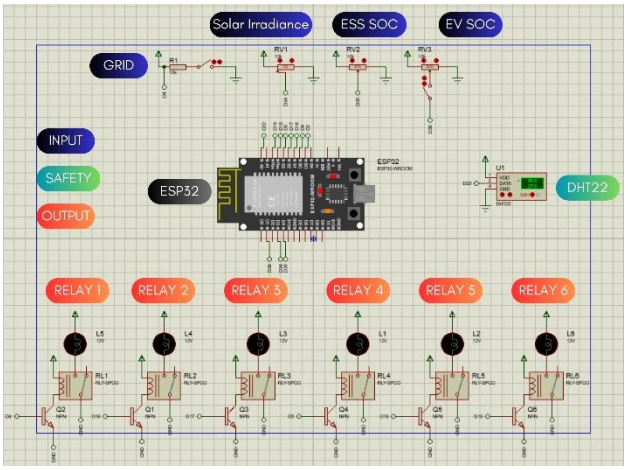


Fig. 4. Schematic diagram of energy management controllers for Bi-directional EV charging systems with safety features.

## IV. Result and Discussion

This section will highlight the contribution to the understanding of Energy Management controllers for Bi- directional EV Charging Systems with Safety Features.

The primary objective was to develop an Energy Management Controller for a V2G Bi-directional charging system with safety features and to validate the prioritized energy distribution algorithm for a Bi-directional EV Charging system on 12 scenarios by evaluating the functionality of components in the proposed micro grid system. Through the analysis, the outcome has been observed by using the Thingsboard platform as a monitoring system dashboard and InfluxDB as a cloud database.

### A. Hardware

Fig. 5 shows the hardware component in the Energy Management Controller for Bi-directional EV Charging System with Safety Features. The controller managed the active relays to work based on the real-time input condition based on 12 Scenarios A to L. The validation of the system working under the real condition of each scenario is in Table III and the average relay switching time is 50ms.

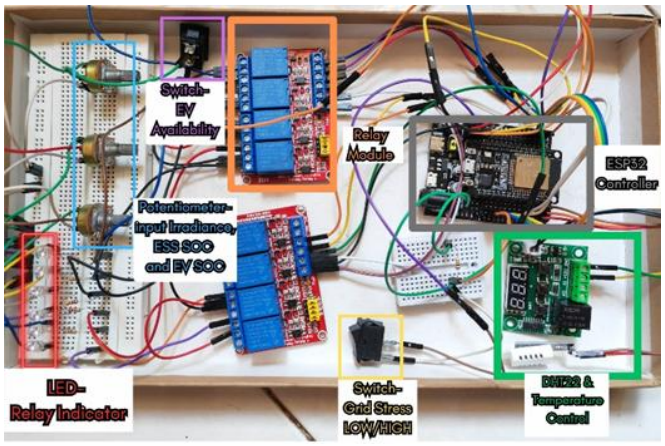


Fig. 5. Hardware component in the system.

TABLE III. List of Scenarios based on the Input Conditions to Determine the Active Relay

| Active Scenario | Input Conditions | Active Relay | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 |
| Safety | Temperature > 50 Celcius | | | | | | |
| A | -Grid Stress: HIGH<br>-Irradiance: > 500<br>-ESS: SOC < 40%<br>-EV: N/A | | | | | √ | |
| B | -Grid Stress: LOW<br>-Irradiance: > 500<br>-ESS: SOC < 40%<br>-EV: SOC < 70% | √ | √ | | | √ | |
| C | -Grid Stress: LOW<br>-Irradiance: > 500<br>-ESS: SOC < 40%<br>-EV: SOC > 70% | √ | √ | √ | √ | √ | |
| D | -Grid Stress: HIGH<br>-Irradiance: > 500<br>-ESS: SOC < 40%<br>-EV: SOC > 70% | | √ | √ | √ | √ | |
| E | -Grid Stress: HIGH<br>-Irradiance: < 500<br>-ESS: SOC < 40%<br>-EV: SOC > 70% | | √ | √ | √ | | |
| F | -Grid Stress: LOW<br>-Irradiance: < 500<br>-ESS: SOC < 40%<br>-EV: SOC < 70% | √ | √ | √ | √ | | |
| G | -Grid Stress: LOW<br>-Irradiance: < 500<br>-ESS: SOC < 40%<br>-EV: SOC < 70% | √ | √ | √ | √ | | |
| H | -Grid Stress: LOW<br>-Irradiance: < 500<br>-ESS: SOC > 40%<br>-EV: SOC < 70% | √ | √ | √ | √ | | |
| I | -Grid Stress: HIGH<br>-Irradiance: < 500<br>-ESS: SOC > 40%<br>-EV: SOC < 70% | | √ | √ | √ | | √ |
| J | -Grid Stress: HIGH<br>-Irradiance: > 500<br>-ESS: SOC > 40%<br>-EV: N/A | | | | | √ | √ |
| K | -Grid Stress: HIGH<br>-Irradiance: < 500<br>-ESS: SOC > 40%<br>-EV: N/A | | | | | | √ |
| L | -Grid Stress: HIGH<br>-Irradiance: > 500<br>-ESS: SOC > 40%<br>-EV: SOC < 70% | | √ | √ | √ | √ | √ |

### B. Monitoring

For monitoring the system, parameters such as temperature, input conditions, active relay, and active scenario, are presented using telemetry. The data from all the sensors are sent to the Thingsboard using the Message Queuing Telemetry Transport (MQTT) communication method. Fig. 6 shows the Thingsboard monitoring dashboard that shows the Input Conditions consisting of Grid Stress, Solar Irradiance value, ESS SOC percentage, and EV SOC percentage, Output Relay consists of Relay 1 until Relay 6, Active Scenario, Current Temperature of the system and the temperature alarm warning. This monitoring is used to validate the relay status according to the power flow.

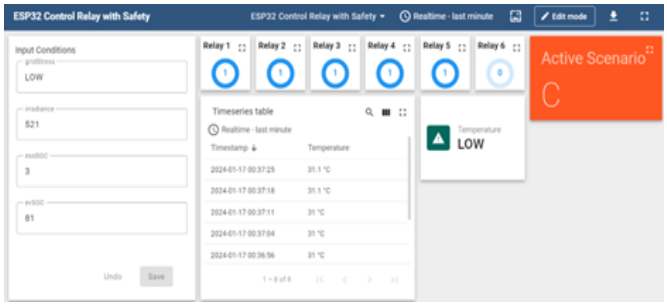


Fig. 6. Thingsboard monitoring dashboard.

### C. Data Storage and Analysis

For data collection and data analysis, the data from the ESP32 controller will be collected using the InfluxDB database platform. Data is stored and visualized through various formats,

including tables, time-series graphs, and histograms. Fig. 7 and Fig. 8 show the data that has been sent to the InfluxDB database, and it can be organized in the form of a table and graph. The data consists of conditions of grid stress, irradiance, ESS SOC, EV SOC, Temperature value, status of relays, and active scenario. InfluxDB allows the users to customize their data based on what the user wants to analyze. The total entries count so far was up to 200 data. The capacity of database storage can be considered based on historical data needs and data granularity.

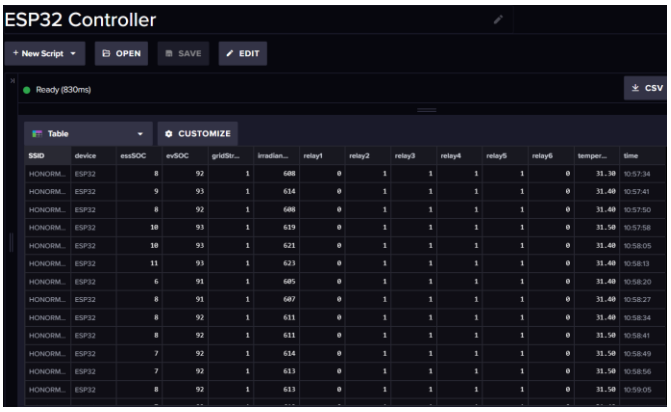


Fig. 7. Data collection of energy management controller for Bi-directional EV charging system with safety features in table.


Fig. 8. Data collection of solar irradiance real-time value in graph.

### D. Energy Management System

The proposed Energy Management Controller is developed to take advantage of renewable energy from the solar system to reduce the dependency on the electrical grid and maximize the usage of renewable energy. This strategic approach aims to minimize the dependency on the Electrical Grid, thereby reducing operational costs and enhancing the overall sustainability of the renewable energy infrastructure.

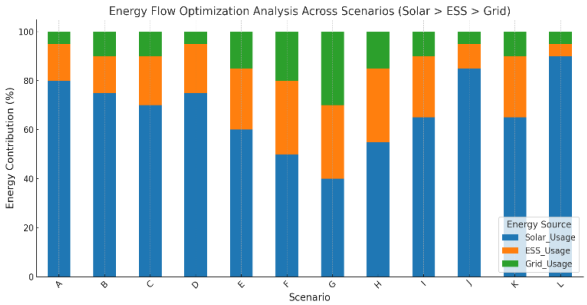


Fig. 9. Energy flow optimization across all scenarios.

In Fig. 9, the system manages energy sources based on predefined scenarios, optimizing renewable energy, and minimizing reliance on the Electrical Grid. Scenarios are designed to consider various factors such as grid stress, irradiance levels, ESS SOC, and EV SOC. Among the 12 possibilities, 50% prioritize the use of renewable energy. Scenarios A, B, C, D, J, and L are precisely designed to benefit solar power for charging both the Energy Storage System (ESS) and Electric Vehicles (EVs).

Conversely, only 42% of scenarios (B, C, F, G, and H) require a partial reliance on the electrical grid. In these cases, the system intelligently determines whether to draw power from the grid to charge the ESS, EVs, or both. The remaining 8% comes from the EV battery. When the EV battery SOC is greater than 70%, the user can discharge to the ESS. This dual-mode operation not only enables flexibility but also a fail-safe mechanism that ensures ongoing operation even in insufficient renewable energy conditions.

As referring to Table IV, scenarios with high solar irradiance, such as A, J, and L**,** rely almost entirely on solar energy, with utilization reaching up to 90%, ensuring minimal dependency on other sources. In contrast, scenarios with lower solar availability, such as E, F**,** and G**,** the ESS contributed significantly (5% to 30%) to support energy demands and reduce grid reliance. Grid usage is kept as the last priority**,** only being utilized when both solar and ESS are insufficient to meet system requirements. This optimized energy distribution strategy maximizes renewable energy utilization**,** enhances energy independence, and ensures minimal reliance on the electrical grid**,** making the system more efficient and sustainable.

In Fig. 10, solar energy sources are the primary energy source during sunny days, peaking at 80% at midday, minimizing reliance on other sources, while gradually decreasing in the morning and late afternoon, requiring support from ESS and the grid. ESS serves as the secondary source, contributing 5% to 15% based on solar availability which is higher during low solar periods (morning/evening) to reduce grid dependence and lower (5%) during peak solar hours to conserve stored energy. Grid is the last priority, used only when both solar and ESS are insufficient, with reliance increasing at night when solar is unavailable, though ESS helps reduce the grid load.

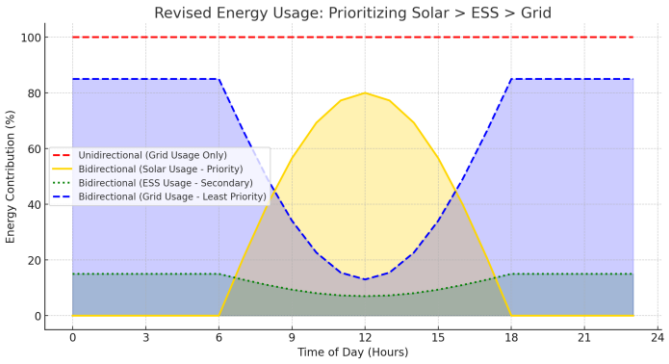


Fig. 10. Energy usage prioritizing solar>ESS>Grid.

TABLE IV. SCENARIO-BASED ENERGY CONTRIBUTION TABLE

| | Solar Irradiance | Grid Stress | ESS SOC | EV SOC | Solar Usage (%) | ESS Usage (%) | Grid Usage (%) | Reasoning |
|---|---|---|---|---|---|---|---|---|
| A | High (>500 W/mÂ²) | High | High (>40%) | N/A | 80 | 15 | 5 | High solar availability enables the system to rely primarily on solar, with ESS providing additional support. Grid is only used as a last resort. |
| B | High (>500 W/mÂ²) | Low | High (>40%) | Low (<70%) | 75 | 15 | 10 | Lower grid stress allows some reliance on the grid, but solar remains the primary source, with ESS supporting when needed. |
| C | High (>500 W/mÂ²) | Low | High (>40%) | High (>70%) | 70 | 20 | 10 | Higher EV SOC enables more discharging to ESS, allowing greater energy flexibility. Solar still dominates; grid remains minimal. |
| D | High (>500 W/mÂ²) | High | High (>40%) | High (>70%) | 75 | 20 | 5 | With high grid stress, reliance on the grid is minimized. Solar is the dominant source, with ESS providing secondary energy supply. |
| E | Low (<500 W/mÂ²) | High | High (>40%) | High (>70%) | 60 | 25 | 15 | Lower solar irradiance requires more support from ESS. Grid is used only when both solar and ESS are insufficient. |
| F | Low (<500 W/mÂ²) | Low | High (>40%) | Low (<70%) | 50 | 30 | 20 | With low grid stress, some grid usage is acceptable. However, ESS takes a larger role due to reduced solar contribution. |
| G | Low (<500 W/mÂ²) | Low | High (>40%) | Low (<70%) | 40 | 30 | 30 | Very low solar irradiance forces higher grid and ESS usage, with grid contributing equally to ESS. |
| H | Low (<500 W/mÂ²) | Low | High (>40%) | Low (<70%) | 55 | 30 | 15 | A balanced approach where ESS supports more than the grid, but solar still plays a significant role in reducing grid dependency. |
| I | Low (<500 W/mÂ²) | High | High (>40%) | Low (<70%) | 65 | 25 | 10 | Since grid stress is high, grid usage is minimized. Solar and ESS work together to supply power efficiently. |
| J | High (>500 W/mÂ²) | High | High (>40%) | N/A | 85 | 10 | 5 | Ample solar availability allows the system to prioritize solar. ESS contributes slightly, while the grid is barely used. |
| K | Low (<500 W/mÂ²) | High | High (>40%) | N/A | 65 | 25 | 10 | Grid usage is minimized due to high stress. ESS helps balance the energy flow with solar taking the lead. |
| L | High (>500 W/mÂ²) | High | High (>40%) | Low (<70%) | 90 | 5 | 5 | Optimal condition where solar is fully utilized, leaving minimal load for ESS and grid. |

While this study does not include direct experimental benchmarking against existing energy management controllers, a qualitative assessment reveals key functional advantages. Many prior systems emphasized hardware-level efficiency improvements [9], [13], [14] or cloud-based interfaces [10], [15] but lacked a unified framework for real-time energy prioritization and integrated safety control. The proposed EMC advances the state-of-the-art by implementing a prioritized energy distribution logic (Solar > ESS > Grid), embedded with a temperature-based relay safety mechanism and validated through a full hardware tested with 12 operational scenarios. These design features collectively contribute to reducing grid dependency, enhancing renewable energy use, and increasing system resilience under fluctuating input conditions.

## V. CONCLUSION

The increasing reliance on grid-dependent EV charging systems has led to high energy costs, grid instability, and inefficient renewable energy utilization, highlighting the need for an intelligent Bi-directional energy management solution. Existing systems lack real-time energy prioritization, failing to dynamically allocate power between solar, ESS, and the grid based on real-time conditions. To address these gaps, this study developed an Energy Management Controller (EMC) implemented on an ESP32 microcontroller, integrating a prioritized Solar to ESS to Grid strategy with a temperature- based safety mechanism to optimize energy flow. The system was tested under 12 predefined operational scenarios, where it successfully reduced grid dependency to 15%, achieved renewable energy utilization of up to 90%, and maintained seamless relay switching. The safety mechanism effectively prevented overheating by shutting down relays when the temperature exceeded 50°C, ensuring stable operation. The EMC's real-time control, validated through ThingsBoard monitoring and InfluxDB data analysis, demonstrated its ability to enhance energy efficiency, lower costs, and improve grid stability in Bi-directional EV charging applications. These results underscore the EMC's potential to revolutionize EV charging infrastructure by minimizing grid reliance and maximizing renewable energy integration, with future work focusing on machine learning-based predictive energy management to further improve performance.

## ACKNOWLEDGMENT

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# Machine Learning-Based Prediction of Cannabis Addiction Using Cognitive Performance and Sleep Quality Evaluations

Abdelilah Elhachimi[1], Mohamed Eddabbah[2], Abdelhafid Benksim[3], Hamid Ibanni[4], Mohamed Cherkaoui[5]*
Department of Biology, University Cadi Ayyad Marrakech (UCAM), Marrakech, Morocco[1, 5]
The Higher School of Technology of Essaouira (ESTE) Cadi Ayyad University, Morocco[2]
Institute of Nursing Professions and Healthcare Techniques (ISPITS), Marrakech, Morocco[3]
National Association of Drug-Risk Reduction (RdR-Maroc), Marrakech, Morocco[4]

***Abstract*—Cannabis addiction remains a growing public health concern, particularly due to its impact on cognition and sleep quality. Conventional screening tools, such as structured interviews and self-assessments, often lack objectivity and sensitivity. This study aims to develop and compare machine learning (ML) models for the prediction of cannabis addiction using cognitive performance (Montreal Cognitive Assessment – MoCA) and sleep quality (Pittsburgh Sleep Quality Index – PSQI) features. A total of 200 participants aged 13 to 24 were assessed, including 103 diagnosed addicts and 97 controls. Principal Component Analysis (PCA) was used to reduce data dimensionality and enhance model robustness. The study evaluated six supervised machine learning algorithms, namely Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Multilayer Perceptron (MLP). Results showed that LR and MLP models achieved high sensitivity (85.71%) and specificity (100%) on the test set, outperforming the DSM-5-based CUD reference test (sensitivity = 71.43%). Although the RF and XGBoost models achieved perfect classification on the training set, their reduced performance on the test set indicates a potential overfitting issue. Integrating machine learning with validated psychometric assessments enables a more accurate and objective identification of cannabis addiction at early stages, thus supporting timely interventions and more effective prevention strategies.**

***Keywords*—Cannabis addiction; machine learning; cognitive assessment; sleep quality; predictive modeling**

## I. Introduction

In recent decades, cannabis use has increased sharply, making it one of the most popular psychoactive substances worldwide. In this context, the United Nations Office on Drugs and Crime (UNODC) released a report in 2022 that outlined drug use trends from 2010 to 2020 [1]. According to this document, the number of individuals aged 15 to 64 who used a psychoactive substance in a given year remained relatively constant compared to previous years, with approximately 284 million people affected, or approximately 5.6% of the global population. Of these users, nearly 13.6%, or 38.6 million people, suffer from a drug use disorder. The report specifies that of these users, 13.6% of them, representing approximately 38.6 million individuals, have a drug use disorder. The report also indicates that cannabis was the most common psychoactive substance, with 209 million users, a significant increase of 23% compared to 2010. This consumption varies significantly by region. A systematic study revealed that the prevalence ranges from 0.42% to 43.90% in Europe, 1.40% to 38.12% in North and South America, 0.30% to 19.10% in Asia, and 1.30% to 48.70% in Oceania and Africa [2]. Numerous studies worldwide have extensively explored the cognitive, psychiatric, physical, and socioeconomic effects associated with cannabis use [3,4]. In this sense, this research has focused on cognitive deficits linked to cannabis use, including effects on executive functions, memory, attention, and decision-making abilities. The cognitive disorders are of greater concern due to their significant impact on the social, academic, and professional lives of those affected, particularly young adults whose cognitive abilities are still developing [5]. Furthermore, many studies highlight that sleep disturbances are generally associated with cannabis addiction. These disturbances concern the duration, quality, and efficiency of sleep [6], [7]. Sleep disturbances have been shown to be a predictive and aggravating factor in cannabis addiction [8], [9]. The sleep disturbance is measured using standardized instruments such as the Pittsburgh Sleep Quality Index (PSQI) [10].

Given these findings, cannabis addiction is often underdiagnosed due to the lack of objective, specific, and easily usable assessment tools for healthcare professionals [11]. Currently, screening for cannabis addiction relies primarily on structured or semi-structured clinical interviews and patient self-assessment [12]. These methods generate a significant amount of subjectivity and are vulnerable to various response biases [13]. Therefore, given these methodological constraints, it would be preferable to use innovative approaches that reliably and objectively identify predictive signs of addiction at their earliest stages. In this sense, artificial intelligence (AI), and more specifically predictive models-based ML, appear to be a promising solution to overcome these limitations. Machine learning offers major advantages, such as the ability to simultaneously analyze a large number of complex variables, identify subtle patterns in clinical and psychometric data, and produce accurate, reproducible predictions that can be generalized to new populations [14]. Indeed, these models are widely used in various fields of health, in diagnostic prediction, risk stratification, and therapeutic personalization [15].

Furthermore, the use of biomarkers such as cognitive status and sleep quality as features in an ML model could be a particularly interesting approach to predict cannabis addiction. Standardized cognitive tests such as the MoCA can offer a rapid, reliable and sensitive measure of global cognitive functions, allowing early detection of alterations associated with regular cannabis use [16]. Similarly, the objective assessment of sleep quality through the PSQI index provides a precise vision of the sleep disturbances often reported by cannabis users, in particular difficulties falling asleep, frequent night awakenings and poor subjective sleep quality [17]. These disorders could constitute interesting markers for early detection of cannabis.

The main objective of this article is to develop, validate, and compare several machine learning approaches to effectively predict cannabis dependence by combining in-depth cognitive assessments with objective measures of sleep quality. Furthermore, the development of a machine learning-based predictive model could provide a clinical decision-making tool for healthcare professionals. These predictive models could facilitate early screening, rapid intervention, and individualized therapeutic management.

This work constitutes an approach aimed at modernizing clinical practices in the field of addiction medicine. It also aims to strengthen primary and secondary prevention programs in the field of addiction medicine. Furthermore, this research can fill significant gaps in the current scientific literature and significantly contribute to improving knowledge regarding the complex interactions between cannabis use, cognitive functioning, and sleep quality. Furthermore, the use of ML in the field of addiction could contribute to the improvement and development of broader preventive strategies based on evidence.

To facilitate understanding and readability, the paper is structured as follows: the next section provides a detailed review of relevant scientific literature, highlighting existing screening methods and the growing interest in machine learning-based approaches for addiction prediction. Subsequently, we describe the methodology, including data collection procedures, evaluation instruments, as well as statistical and machine learning techniques employed. The results section presents a comparative analysis of the performances achieved by different machine learning models, while the discussion section provides an in-depth interpretation of these findings, placing them in context with previous research and emphasizing their clinical implications. Finally, the conclusion summarizes the primary contributions of this study, acknowledges its limitations, and outlines avenues for future research.

## II. Literature Review

Screening cannabis addiction represents a significant public health challenge, particularly given its growing global prevalence. Traditional diagnostic methods have shown limitations, prompting the exploration of advanced approaches such as ML. Over recent years, ML has become transformative in addiction research, enabling detailed analyses and predictions of addictive behaviors and treatment outcomes. For example, Likhith et al. [18], successfully applied ML algorithms to predict smartphone addiction by analyzing behavioral indicators like app usage patterns, notification-checking frequency, and psychological factors such as stress and anxiety. Similarly, Kumara et al. [19], utilized ML models, including Random Forest (RF) and Convolutional Neural Networks (CNN), to accurately identify addiction risk factors, addiction types, and relapse probabilities, significantly enhancing prevention and treatment efficacy.

In clinical addiction research, diverse data sources have been leveraged to build predictive models that enhance risk assessment and treatment outcomes. Feng et al. [20], utilized neuroimaging data derived from functional Magnetic Resonance Imaging (fMRI) to predict symptoms of internet addiction, identifying distinct connectivity patterns in brain networks associated with addiction-related behaviors. Likewise, Pyzowski et al. [21], demonstrated that electronic medical records and prescription drug monitoring data could effectively be integrated into machine learning frameworks to predict opioid addiction risk, highlighting factors such as psychiatric history and socioeconomic background. The same authors also demonstrated the utility of clinical laboratory data, including patient adherence and buprenorphine treatment outcomes, in predicting short-term relapse, thereby providing actionable insights for clinicians.

Additionally, recent studies explored innovative applications of ML models using alternative data sources, such as social media and self-reported surveys. Yang et al. [22], applied sentiment analysis using advanced Generative Adversarial Networks (GANs) on social media data, successfully predicting opioid relapse by identifying emotional triggers such as negativity or anxiety. Similarly, surveys capturing demographic data, phone usage behaviors, and psychological measures (e.g., stress or anxiety) have effectively predicted behavioral addictions, enabling early intervention strategies [18].

Furthermore, ML techniques have shown promise in distinguishing behavioral addictions like Internet gaming disorder from substance use disorders. Lee et al. [23], demonstrated the effectiveness of multimodal approaches combining neuropsychological assessments with Electroencephalography (EEG) features, achieving accuracy rates exceeding 70%. Such data-driven computational methods offer valuable insights into neural mechanisms underlying addictive behaviors, potentially informing targeted therapeutic interventions [24].

Despite these advancements, significant challenges remain. Bouhadja and Bouramoul [25], highlighted the critical role of data quality and diversity, emphasizing the need for robust, structured datasets to enhance predictive reliability. Unfortunately, the scarcity of comprehensive datasets remains a major hurdle in addiction research, often leading to overfitting and limited generalizability of ML models [26]. Moreover, methodological inconsistencies across studies, such as variability in study design and analysis methods, continue to pose barriers to reproducibility and validation of ML-derived predictions [27].

Another critical limitation identified in existing literature is the interpretability of ML models. Suva and Bhatia [28], noted that many ML algorithms function as "black boxes," making it difficult for clinicians to trust and implement their recommendations in real-world settings. In addition, ethical issues surrounding the use of sensitive personal data, including

risks of privacy breaches or misuse, remain prominent concerns in deploying these technologies clinically [29]. Finally, Bouhadja and Bouramoul [25], observed that models trained on specific populations may not generalize effectively to diverse clinical contexts, limiting their overall applicability.

Addressing these challenges requires concerted efforts to standardize methodologies, enhance data collection and preprocessing techniques, and improve model transparency. Integrating objective, clinically validated biomarkers such as cognitive performance and sleep quality indicators into predictive ML models may further improve accuracy and clinical utility. Studies by Ewert et al. [16], and Edwards and Filbey [10], have already emphasized cognitive impairment and sleep disturbances as reliable, objective markers associated with cannabis misuse, underscoring their potential value in predictive modeling for addiction.

In summary, advancing ML methodologies by addressing existing limitations can significantly enhance cannabis addiction screening, supporting early intervention and personalized treatment strategies. The current study aims precisely to contribute to these advancements, by proposing a robust ML-based predictive framework utilizing validated psychometric tools.

## III. Methodology

### A. Population Study

A population of 200 participants from both genders, aged between 13 to 24 years old, and who agreed to participate in this study. The sample of the study comprises two groups: 1) 103 participants clinically identified as cannabis addict; 2) 97 control patients without cannabis addiction.

The exclusion criteria included 1) patient refusing to participate in the study, 2) patient with serious behavioral issues who were unable to respond to the questions, 3) patients who, in addition to cannabis, were addicted to other psychoactive drugs.

This study was conducted at the primary health center for addiction in Marrakech. The study was authorized by the regional health directorate. The procedures were conducted in accordance with the guidelines of the Declaration of Helsinki. All participants were informed prior to data collection about the purpose of the study. Every participant and/or their legal representative has given their written informed consent.

### B. Data Collection

Following a consultation with the psychiatrist-addictologist of Marrakech, an anonymous questionnaire is used to collect data aimed at obtaining information on the sociodemographic, clinical, cognitive and sleep quality characteristics of the study population.

*1) The Montreal Cognitive Assessment (MoCA)* test is a clinical neuropsychological test used to assess cognitive impairment. It consists of assessments of executive, visuo-spatial, denominative, memory, attention, language, abstraction, recall and orientation functions (Table I). The highest possible score is 30 points. When the score does not exceed the threshold of 26, the patient is identified as having a cognitive impairment [30].

TABLE I. Detailed Composition and Scores Associated with the MoCA Cognitive Assessment Test

| Attribute Name | Component | Points Assigned |
|---|---|---|
| MoCA1 | Visuospatial / Executive | 5 points |
| MoCA2 | Naming (Denomination) | 3 points |
| MoCA3 | Attention | 6 points |
| MoCA4 | Language | 3 points |
| MoCA5 | Abstraction | 2 points |
| MoCA6 | Memory | 5 points |
| MoCA7 | Orientation | 6 points |
| MoCA | Total Score MoCA | 30 points |

*2) The Pittsburgh Sleep Quality Index (PSQI)* is a test used to assess sleep quality**.** Consisting of 11 questions with a maximum score of 21, aimed at quantifying sleep efficiency and quality. Each item is rated from 0 to 3, and the sum of the scores from the seven components constitutes the global PSQI score, which ranges from 0 to 21 (Table II). A global PSQI score above 5 reflects poor sleep quality [31].

TABLE II. Components and Scoring System of the Pittsburgh Sleep Quality Index (PSQI)

| Attribute Name | Component | Description | Score (0-3) |
|---|---|---|---|
| PSQIC1 | Subjective Sleep Quality | Overall perception of sleep quality | 0 = Very good<br>3 = Very poor |
| PSQIC2 | Sleep Latency | Time taken to fall asleep | 0 = <15 min<br>3 = >60 min |
| PSQIC3 | Sleep Duration | Total sleep hours per night | 0 = >7h<br>3 = <5h |
| PSQIC4 | Sleep Efficiency | Ratio of sleep time to time in bed | 0 = >85%<br>3 = <65% |
| PSQIC5 | Sleep Disturbances | Frequency of sleep interruptions and issues | 0 = None<br>3 = Daily |
| PSQIC6 | Use of Sleep Medication | Frequency of sleeping pill use | 0 = Never<br>3 = Daily |
| PSQIC7 | Daytime Dysfunction | Impact of sleep deprivation on daily activities | 0 = None<br>3 = Severe |

*3) Cannabis Use Disorder (CUD)* is a set of guidelines issued by the American Psychiatric Association to characterize problematic cannabis use in cognitive-behavioral, psychological and environmental terms. A score below 2 indicates no addiction, a score between 2 and 3 indicates mild addiction, a score between 4 and 5 indicates moderate addiction, and a score above 6 indicates severe addiction [32].

Participants with a cannabis addiction are identified and diagnosed using this DSM-5 questionnaire. Participants are divided into two classes: 0: Non-Addict and 1: Addict. All addicts, regardless of the intensity of their addiction, are included in the addict class. The gold standard for comparing the acquired models is the CUD questionnaire.

Analysis of the addictive profile according to DSM-5 criteria in our sample reveals a marked split between non-addicts and those with varying degrees of cannabis addiction. Among the participants, 46% (92 individuals) showed no signs of addiction, while 54% had some form of dependence: 18% suffered from mild addiction (36 individuals), 28% from moderate addiction (56 individuals) and 8% from severe addiction (16 individuals). These results indicate a significant prevalence of problematic cannabis use in our study population. Statistical analysis using the Chi-square test ($\chi^2 = 182.762$, $p < 0.001$) revealed a highly significant association between cannabis use and the development of a DSM-5 addictive disorder. The p-value of less than 0.001 confirms that this relationship is not due to chance, and suggests a direct link between consumption and dependence.

Looking at the distribution of addiction levels, it appears that all cases of moderate and severe addiction exclusively concern cannabis users. What's more, only 5.2% of individuals with mild addiction are classified as non-users, confirming that cannabis addiction is virtually non-existent among non-users; these results underline the high risk of dependence among users, with a high proportion of moderate to severe cases (36%), suggesting that regular use can lead to worsening addiction.

### B. Feature Engineering

The input features consisted of 14 standardized sub-scores: seven from the MoCA (MoCAC1–MoCAC7) and seven from the PSQI (PSQIC1–PSQIC7), capturing key aspects of cognitive performance and sleep quality. All variables were normalized using z-score standardization to ensure comparability and facilitate model convergence.

PCA was applied exclusively to the training data to prevent information leakage. The first three components, which accounted for approximately 53% of the total variance, were retained for comparison purposes. Both original and PCA-transformed feature sets were fed into identical machine learning pipelines, allowing a controlled evaluation of their impact on classification performance.

### C. Machine Learning Models

ML is a tool that allows a machine to acquire knowledge, build models, and analyze complex datasets without direct human intervention [33]. In this sense, ML has been widely used recently in many biomedical fields, including psychiatry and addiction [34], [35]. In general, the types of ML algorithms used in addiction research can be grouped as follows: supervised learning, unsupervised learning, deep learning (DL), and reinforcement learning (RL) [36].

In this study, six supervised machine learning algorithms were trained to predict cannabis addiction using cognitive and sleep quality features. All models were evaluated under two conditions: using the original standardized feature set and using the PCA-transformed data. This dual evaluation allowed us to assess the effect of dimensionality reduction on model performance.

*1) Logistic regression:* Logistic regression (LR) is a very popular supervised ML model. It is used to predict a categorical dependent variable from a set of explanatory variables [37]. LR calculates the probability that an observation belongs to a particular class [38]. In this paper, the LR model is configured without intercepts and with a linear solver "liblinear".

*2) K-Nearest neighbors:* The K-Nearest Neighbors (KNN) algorithm consists of calculating the distance between an unknown data point and its "k" nearest neighbors already classified. Subsequently, the label of the nearest class is assigned to the observation. The performance of the algorithm depends on the number of neighbors selected (k=1, 2, 3, ...), as well as the chosen distance (Euclidean, Manhattan, etc.)[39]. In this study, the optimization of the model focused on the choice of the number of neighbors (19, 21 and 23) to ensure robust decision-making, as well as on uniform weighting to simplify interpretation. The Manhattan distance was chosen as the metric because it is suitable for heterogeneous data and less sensitive to scale variations [40].

*3) Support vector machine:* The Support Vector Machine (SVM) is a robust linear classifier capable of distinguishing different classes from input data. Although there are infinitely many linear separators for classification problems, the SVM chooses an optimal one, ensuring maximum spacing between classes [41]. We used the Support Vector Machine (SVM) algorithm to classify addiction risk by optimizing its hyperparameters. The penalty C (0.1, 1, 10) was adapted to balance the separation margin and classification errors. Two kernels were tested: linear, suitable for separable data, and RBF, allowing to model complex relationships.

*4) Random forest:* Random forest (RF) is a series of decision trees built from a randomly selected subset of the training data. Each tree is built from a distinct portion of the data and participates in the final decision through a majority vote [42]. The model was parameterized with a number of trees varying between 50, 75 and 100, a maximum depth of 3, and feature selection based on the square root of the total number of explanatory variables (max_features = 'sqrt'). In addition, the minimum node split criterion was tested with 25 and 30 observations.

*5) XGBoost:* XGBoost is an improved model of the gradient boosting algorithm. In ML, extreme gradient boosting is a method that is used to reduce the number of errors in predictive data analysis [43], [44]. XGBoost is an assembly of decision trees that predict residuals and correct the errors of previous decision trees [45]. The particularity of this algorithm is the improvement in accuracy and execution speed. It uses advanced techniques like L1 and L2 regularization, subsampling, and missing value handling to improve its performance [44]. In this paper, the XGBoost model is configured with a number of estimators varying between 50, 75, and 100, a maximum depth of 2, a learning rate from 0.005 to 0.01, and subsampling of features and observations varying between 0.6 and 0.8 to reduce overfitting.

*6) MLP Neural network:* The MLP Neural Network model is an architecture based on the use of multilayer neural networks (Multilayer Perceptron) capable of modeling complex functions thanks to a hierarchy of interconnected hidden layers[46]. In this paper, the MLP network architecture was intentionally simplified to reduce its complexity and limit

overfitting. Three hidden layer sizes (10, 15, and 20 neurons) were tested. Two activation functions (relu and tanh) were evaluated, as well as the adam optimization algorithm for its speed and stability. Regularization was adjusted via the alpha parameter with three values (0.1, 0.5, 1.0) to control the model complexity. Finally, an initial learning rate of 0.001 was used to ensure stable convergence.

### D. Experimental Design and Evaluation Strategy

The dataset was split into a training set (80%) and an independent test set (20%) using stratified sampling to preserve class distribution. All data preprocessing steps, including z-score standardization and dimensionality reduction via PCA, were strictly performed after the train-test split, and fitted exclusively on the training set to prevent data leakage. The PCA was applied on the correlation matrix of the training data, and the first three components were retained, accounting for approximately 53% of the total variance. This choice aimed to reduce dimensionality while preserving relevant variance and enabling visual analysis. PCA-transformed data were used for comparison with the full-feature models.

In addition to this train–test evaluation, we implemented a 5-fold stratified cross-validation on the training data to assess model robustness and generalization. Performance metrics accuracy, sensitivity, specificity, and AUC were computed on each fold and averaged. Standard deviations were also calculated to evaluate metric stability across folds.

Final validation was conducted on the unseen 20% test set. Although confusion matrices were generated for Random Forest and XGBoost for visualization purposes, the model evaluation relied exclusively on three key indicators: sensitivity, specificity, and precision. These metrics were selected for their clinical interpretability and direct relevance to addiction screening, and were compared to the reference diagnostic criteria of the CUD-DSM5, used as the gold standard. Additionally, ROC curves and AUC values were computed to assess the global discriminatory power of each classifier.

All experiments were conducted using Python 3.10, with scikit-learn (v1.2), XGBoost (v1.7), pandas (v1.5), and numpy (v1.23). A random seed (42) was fixed for reproducibility. Where applicable, hyperparameter tuning was performed using grid search, and class imbalance was handled using class_weight='balanced'.

*1) ROC curve:* The ROC curve is a graphical representation that shows the sensitivity and specificity for all possible classification threshold values. It is a visual device that helps to establish a balance between true positives and false negatives [47]. The closer the curve is to the upper left corner implies a better quality of the model.

*2) AUC metric:* AUC is a numerical indicator obtained based on the ROC curve. It illustrates the chance that the model produces the correct prediction based on a specific threshold and chosen attributes [48]. The closer it is to 1, the better the model will perform.

*3) Test validity:* Sensitivity and specificity are two statistical criteria used to assess a test's validity [49], [50]. The ratio of actual diseased patients to all diseased patients is known as the sensitivity [51]. The test's sensitivity shows how well it can identify patients who are ill [49]. Conversely, specificity is defined as the proportion of real healthy patients who are not recognised among all healthy patients[51]. The test's specificity shows how well it can rule out healthy people [49]. Another metric, such as accuracy, which is the proportion of all correct hits among all participants, can also be used to solidify the validity [49].

## IV. Results

Exploratory Data Analysis (EDA) was organized in two parts: on the one hand, the evaluation of continuous variables such as age, Age of first Cannabis Use (AFCU), Cannabis Use Duration(CCD), MoCA, and PSQI scores, using the Kolmogorov-Smirnov (KS) test to test normality and the Mann-Whitney U test to compare distributions between addicted and non-addicted groups; On the other hand, the analysis focused on the cognitive components of the MoCA and the sleep quality parameters of the PSQI in order to highlight the statistical differences and their relevance in determining the addictive disorder. This methodology makes it possible to identify the most discriminating cognitive and behavioral markers, thus contributing to a better understanding and modeling of the risk of addiction. The Kolmogorov-Smirnov (KS) test was used to assess the normality of variable distributions in the addict and non-addict groups. A p-value $< 0.05$ indicates a significant deviation from a normal distribution, meaning that the variable does not follow a normal distribution (Table III).

The results in Table III shows that most variables are significantly different ($p < 0.01$) between the groups, indicating notable impacts of cannabis addiction on cognition and sleep quality. Indeed, scores on the various MoCA components were significantly lower in addicts, except for the abstraction component, which was not significant ($p = 0.054$). Furthermore, the total MoCA score is highly significant ($p < 0.01$), implying an overall impairment of cognitive functions in addicts. Regarding the PSQI, most PSQI components showed significant differences ($p < 0.01$), suggesting impaired sleep quality in addicts. Furthermore, the Sleep Duration component ($p = 0.182$) was not significant, indicating that sleep duration did not differ significantly between groups.

These results reinforce the idea that cannabis addiction negatively impacts cognitive function and sleep quality, although some aspects (abstraction and sleep duration) appear to be less affected. In this sense, PCA was therefore used to reduce the dimensionality of the dataset while retaining essential information from the MoCA and PSQI subcomponents. Applying PCA allows these subcomponents to be transformed into a reduced number of non-redundant variables, while maximizing the explained variance. The dimensionality reduction will allow the elimination of highly correlated variables to avoid information redundancy, the extraction of the main axes underlying cognitive deficits and sleep disorders in addicts, and the improvement of the efficiency of machine learning models by reducing the risk of overfitting.

TABLE III. COMPARATIVE ANALYSIS OF COGNITIVE AND SLEEP PARAMETERS BETWEEN ADDICTS AND NON-ADDICTS USING THE MOCA AND PSQI TEST

| | Non-addict | | | Addict | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Means ±SD** | **KS** | **p-value** | **Means±SD** | **KS** | **p-value** | **Mann-Whitney U** | **Z** | **p-value** |
| Age | 20.08±2.11 | 0.21 | <0.01 | 21.23±2.84 | 0.238 | <0.01 | 6323.5 | 3.272 | 0.001 |
| AFCU | 2.41±5.48 | 0.505 | <0.01 | 15.75±2.46 | 0.223 | <0.01 | 9352.5 | 11.068 | <0.01 |
| CCD | 00 | 00 | 00 | 4±2.2 | 0.204 | <0.01 | 9991.0 | 13.010 | <0.01 |
| **TEST MoCA** | | | | | | | | | |
| Visuospatial/ executive | 4.55±0.48 | 0.383 | <0.01 | 4,05±0.84 | 0.22 | <0.01 | 3310.5 | -4.490 | <0.01 |
| Naming | 3±0.00 | | | 2.88±0.32 | 0,52 | <0.01 | 4413.5 | -3.459 | <0.01 |
| Attention | 4,23±0,62 | 0,31 | <0.01 | 3,79±0,97 | 0,24 | <0.01 | 3684.0 | -3.485 | <0.01 |
| Language | 2,95±0.22 | 0,54 | <0.01 | 2,5±0,56 | 0,34 | <0.01 | 2820.5 | -6.856 | <0.01 |
| Abstraction | 1,33±0,56 | 0,43 | <0.01 | 1,17±0,55 | 0,37 | <0.01 | 4348.5 | -1.925 | 0.054 |
| Memory | 4,40±0,55 | 0,34 | <0.01 | 3,46±0,86 | 0.30 | <0.01 | 2041.0 | -7.895 | <0.01 |
| Orientation | 5,95±0.2 | 0,54 | <0.01 | 5,72±0,45 | 0,46 | <0.01 | 3843.5 | -4.435 | <0.01 |
| MoCA | 26,40±1,06 | 0,22 | <0.01 | 23,58±2,74 | 0,18 | <0.01 | 1445.5 | -8.805 | <0.01 |
| **TEST PSQI** | | | | | | | | | |
| Subjective sleep quality | 1,10 ±0,74 | 0,29 | <0.01 | 1,40 ±0,67 | 0,31 | <0.01 | 6203.0 | 3.213 | 0.001 |
| Sleep latency | 1,41±0,79 | 0,31 | <0.01 | 2,17±0,70 | 0,26 | <0.01 | 7522.5 | 6.553 | <0.01 |
| Sleep duration | 1,05±0,72 | 0,32 | <0.01 | 0,80±0,60 | 0,36 | <0.01 | 4537.0 | -1.336 | 0.18 |
| Habitual sleep efficiency | 0,50±0.87 | 0,41 | <0.01 | 0,96±1.1 | 0,24 | <0.01 | 6736.5 | 4.651 | <0.01 |
| Sleep disturbances | 1,25±0,61 | 0,38 | <0.01 | 1.6 ±0,61 | 0,30 | <0.01 | 6463.5 | 4.038 | <0.01 |
| Use of sleeping medication | 0,14 ± 0.43 | 0.50 | <0.01 | 1,32±1.1 | 0.20 | <0.01 | 8105.5 | 8.527 | <0.01 |
| Daytime dysfunction and sleepiness | 0,90±0.85 | 0.24 | <0.01 | 1,46 ± 0.8 | 0.24 | <0.01 | 6726.5 | 4.468 | <0.01 |
| PSQI | 6,37±2,83 | 0,16 | <0.01 | 10,02±3,57 | 0,12 | 0,001 | 8037.0 | 7.474 | <0.01 |

M ± SD: Mean ± Standard Deviation., KS (D): Kolmogorov-Smirnov test statistic; (p < 0.05 indicates a significant deviation from normality).

The Mann-Whitney test comparing the Addict and Non-Addict groups. A p-value < 0.05 indicates a significant difference between groups; The Z value represents the standardized statistic of the Mann-Whitney U test

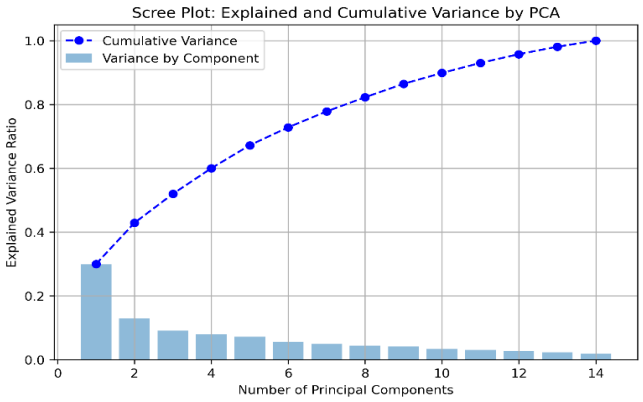


Fig. 1. Distribution of the variance explained and cumulative by the principal components from PCA.

Analysis of explained variance reveals that the first components express a large part of the variance (Fig. 1). Indeed, it is necessary to faithfully represent the data. In addition, the cumulative variance shows the progressive accumulation of explained variance. With 7 to 8 components, about 80% of the total variance is captured, indicating that a large part of the information is preserved. Beyond 10 components, the curve reaches a plateau within 100%, indicating that the last components bring little new information. The first component captures a significant part of the information (about 30%), followed by the second, which captures about 15%. The following components have a decreasing contribution, suggesting that only a few principal components are involved.

The Fig. 2 represents the projection of individuals into the space of the first three principal components resulting from the PCA. Each point corresponds to an individual, with a distinction between non-addicts (in blue) and addicts (in red). The observation shows that the two groups (addicts and non-addicts) occupy relatively distinct regions, although some areas present an overlap. Thus, the first three principal components express a significant part of the total variance, showing a separation between the groups in three dimensions. Furthermore, a more marked concentration of red and blue points in certain regions implies that the PCA has succeeded in capturing structural differences between the groups. The separation between the groups indicates that the principal components contain relevant discriminating information for the prediction of the diagnosis (addict vs. non-addict). However, the presence of an overlap states that some individuals are more difficult to classify, justifying the use of more complex models to improve accuracy. The obtained projection justifies the use of PCA in the preprocessing step for ML.

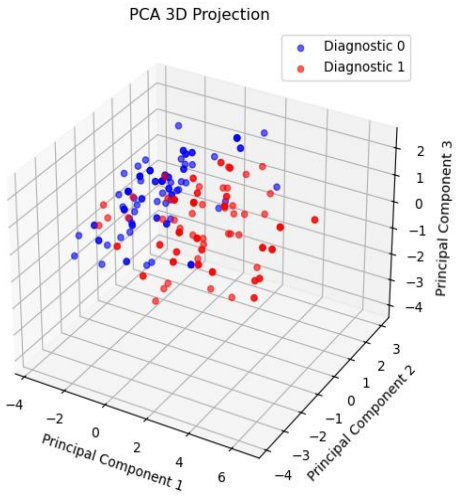


Fig. 2. Projection of individuals into the PCA component space according to addictive status.

In summary, the EDA highlighted redundancies and overlaps between some variables, justifying the application of ACP to better structure the information. In this sense, feature engineering focused on the selection of relevant indicators related to cognitive functions and sleep quality (MoCA and PSQI), with the aim of improving both the robustness and interpretability of the model. The performance of the models is assessed by exploiting the ROC curves shown in Fig. 3.

The results shows that all the tested models reveal an excellent classification capacity, with AUC values greater than 0.90. Indeed, on the test set, the best performances are obtained by the LR and the MLP neural network, both reaching an AUC of 0.94, closely followed by the RF (AUC = 0.93) and the SVM (AUC = 0.92).

These results show that the chosen variables, in particular the principal components resulting from the PCA, are congruent for the discrimination between addicted and non-addicted individuals. Regarding performance on the training set, the most complex models, such as RF (AUC = 0.97) and SVM (AUC = 0.96), have a very high learning capacity. Additionally, these two models show a more marked discrepancy with the results obtained on the test set, which may indicate overfitting. However, RL and the MLP neural network present stable and balanced results between training and testing, reflecting good generalization capacity.

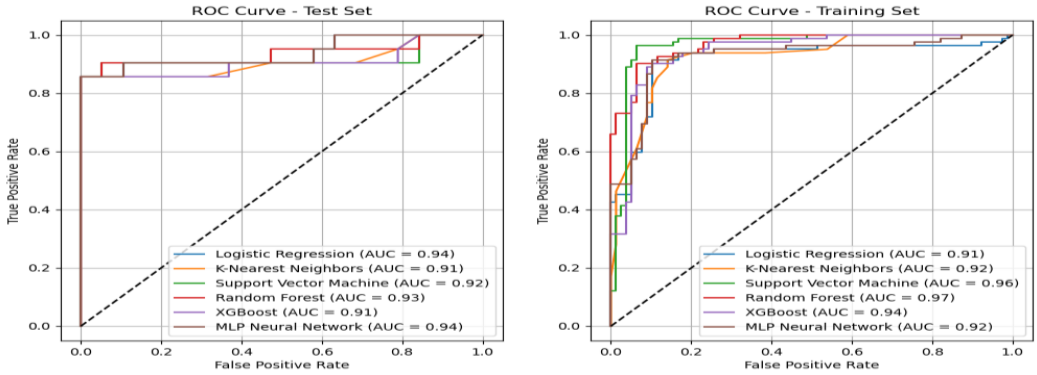


Fig. 3. ROC Curves for classification models on training and test sets for cannabis addiction prediction.

These observations indicate that all models perform well, but the most balanced approaches, such as an MLP can be favored for a robust practical implementation and reliable prediction of cannabis addiction risk.

Table IV summarizes the sensitivity, specificity, and accuracy of six machine learning models (LR, KNN, SVM, RF, XGBoost, and MLP Neural Network) compared to the clinical reference test (CUD-DSM5). Evaluations were conducted on both training and test datasets. On the test set, all models exhibited a specificity of 100%, indicating an excellent ability to correctly identify non-addicted individuals. However, sensitivity varied significantly across models, highlighting differences in their capacity to detect addicted subjects accurately.

The RF classifier demonstrated the highest performance on the test set, with a sensitivity of 90.48% and an accuracy of 95%, closely followed by LR and MLP Neural Network, each achieving sensitivities of 85.71% and accuracies of 92.5%. In contrast, the CUD-DSM5 clinical test, serving as the gold standard, had notably lower sensitivity (71.43%) and accuracy (85%), indicating a potential limitation in reliably identifying individuals with cannabis addiction.

Certain models, such as RF and XGBoost, achieved perfect performance on the training data but showed decreased performance on the test data, suggesting overfitting and thus limiting their practical applicability. Conversely, LR and the MLP Neural Network showed consistent performance between training and testing phases, highlighting their stability and suitability for real-world applications.

Overall, these results underscore that machine learning models significantly outperform the conventional CUD-DSM5 clinical screening tool in detecting cannabis addiction. LR and MLP models emerge as particularly reliable and generalizable options, combining high predictive accuracy with strong robustness.

To further examine the classification behavior of the best-performing models, confusion matrices were generated for Random Forest and XGBoost, both trained on PCA-transformed features (Fig. 4). These matrices display the number of true and false classifications for both training and test sets.

TABLE IV. COMPARATIVE PERFORMANCE METRICS (SENSITIVITY, SPECIFICITY, AND ACCURACY) OF MACHINE LEARNING MODELS VERSUS THE CUD-DSM5 REFERENCE TEST ON TRAINING AND TEST DATASETS

| | Sensitivity | | Specificity | | Accuracy | |
|---|---|---|---|---|---|---|
| | Train (%) | Test (%) | Train (%) | Test (%) | Train (%) | Test (%) |
| **LR** | 87.8 | 85.71 | 87.18 | 100.0 | 87.5 | 92.5 |
| **KNN** | 96.34 | 76.19 | 89.74 | 100.0 | 93.13 | 87.5 |
| **SVM** | 93.9 | 80.95 | 88.46 | 100.0 | 91.25 | 90.0 |
| **RF** | 100.0 | 90.48 | 100.0 | 100.0 | 100.0 | 95.0 |
| **XGBOOST** | 100.0 | 80.95 | 100.0 | 100.0 | 100.0 | 90.0 |
| **MLP** | 90.24 | 85.71 | 89.74 | 100.0 | 90.0 | 92.5 |
| **CUD** | 69.51 | 71.43 | 100.0 | 100.0 | 84.38 | 85.0 |

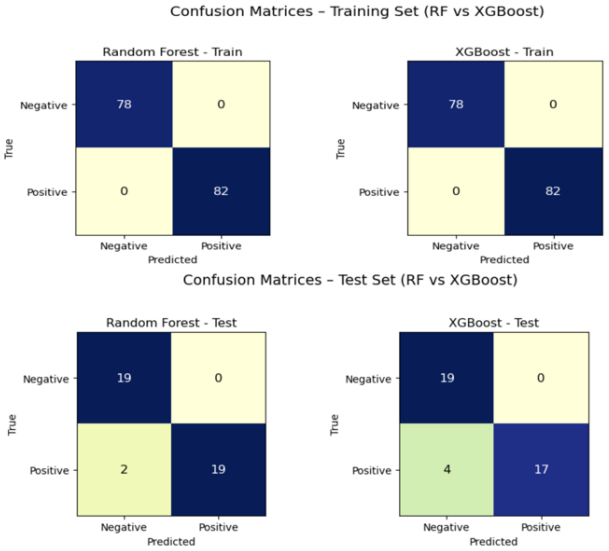


Fig. 4. Confusion matrices for training and test sets: comparison between random forest and XGBoost models.

On the training data, both models achieved perfect classification: all positive and negative cases were correctly identified, yielding 100% sensitivity and 100% specificity.

On the test set, both classifiers maintained perfect specificity (no false positives). However, some false negatives were observed: RF misclassified two positive cases (sensitivity = 90.48%), and XGBoost misclassified four (sensitivity = 80.95%). Accuracy on the test set was 95.0% for Random Forest (95% CI: 83.50% to 98.62%) and 90.0% for XGBoost (95% CI: 76.95% to 96.04%).

These results suggest that while both models effectively avoided false alarms, RF provided a slightly better recall and generalization on unseen data compared to XGBoost.

To evaluate the generalization performance of the classification models, a 5-fold cross-validation was conducted using both the original standardized features and the PCA-transformed components. Table V summarizes the average performance across folds, including accuracy, sensitivity, specificity, and AUC, each reported with their corresponding standard deviation.

Among the models trained on the raw feature set, RF achieved the best overall performance with an average accuracy of 0.938 ± 0.034, sensitivity of 0.915 ± 0.049, specificity of 0.962 ± 0.031, and an AUC of 0.985 ± 0.022. XGBoost followed closely, showing the highest sensitivity (0.927 ± 0.045) and a strong AUC (0.970 ± 0.033), suggesting its effectiveness in detecting positive cases. The MLP classifier also demonstrated competitive performance, with an AUC of 0.968 ± 0.039.

When PCA was applied prior to training, a slight decrease in performance was observed across most models. For instance, the AUC for RF (PCA) dropped to 0.967 ± 0.035, and for XGBoost (PCA) to 0.941 ± 0.030. The decline was more pronounced for models such as LR (PCA) and MLP (PCA), where sensitivity and AUC values were considerably lower compared to their raw counterparts.

These results indicate that while PCA offers a reduction in dimensionality, it does not necessarily improve classification performance. Models trained on the full standardized feature set consistently outperformed those using the reduced component space.

TABLE V. 5-FOLD CROSS-VALIDATED CLASSIFICATION PERFORMANCE OF MACHINE LEARNING MODELS WITH AND WITHOUT PCA. MEAN ± STANDARD DEVIATION (SD) ARE REPORTED FOR EACH METRIC

| Models | Accuracy (±SD) | Sensitivity (±SD) | Specificity (±SD) | AUC (±SD) |
|---|---|---|---|---|
| **RF(Raw)** | 0.938 ± 0.034 | 0.915 ± 0.049 | 0.962 ± 0.031 | 0.985 ± 0.022 |
| **XGBoost (Raw)** | 0.931 ± 0.050 | 0.927 ± 0.045 | 0.937 ± 0.068 | 0.970 ± 0.033 |
| **LR (Raw)** | 0.856 ± 0.058 | 0.842 ± 0.097 | 0.873 ± 0.079 | 0.936 ± 0.054 |
| **SVM (Raw)** | 0.919 ± 0.054 | 0.879 ± 0.098 | 0.962 ± 0.050 | 0.973 ± 0.030 |
| **KNN (Raw)** | 0.856 ± 0.058 | 0.793 ± 0.122 | 0.924 ± 0.047 | 0.949 ± 0.039 |
| **MLP (Raw)** | 0.925 ± 0.061 | 0.926 ± 0.060 | 0.923 ± 0.101 | 0.968 ± 0.039 |
| **RF(PCA)** | 0.912 ± 0.070 | 0.915 ± 0.063 | 0.911 ± 0.084 | 0.967 ± 0.035 |
| **XGBoost (PCA)** | 0.875 ± 0.059 | 0.866 ± 0.089 | 0.884 ± 0.064 | 0.941 ± 0.030 |
| **LR (PCA)** | 0.850 ± 0.054 | 0.843 ± 0.081 | 0.859 ± 0.061 | 0.916 ± 0.053 |
| **SVM (PCA)** | 0.887 ± 0.058 | 0.926 ± 0.062 | 0.846 ± 0.065 | 0.901 ± 0.043 |
| **KNN (PCA)** | 0.856 ± 0.070 | 0.852 ± 0.117 | 0.859 ± 0.024 | 0.923 ± 0.022 |
| **MLP (PCA)** | 0.869 ± 0.054 | 0.877 ± 0.089 | 0.859 ± 0.061 | 0.889 ± 0.074 |

## V. DISCUSSION

This study demonstrates the potential of machine learning (ML) to enhance early screening for cannabis addiction by leveraging objective measures from standardized cognitive and sleep quality assessments. The integration of features from the MoCA and PSQI allowed the ML models to identify addiction-related patterns with high accuracy.

Our results reveal that LR and the MLP achieved the most balanced performance on the independent test set, with sensitivity and specificity both reaching 85.71% and 100%, respectively. These models outperformed the CUD-DSM5 gold standard, which reached only 71.43% sensitivity. This suggests that ML models can detect subtle psychometric variations associated with cannabis addiction that conventional tools may overlook.

Despite the high training accuracy observed in RF and XGBoost models (100%), their performance dropped on the test set (sensitivity = 90.48% and 80.95%, respectively), revealing overfitting. This highlights the necessity of cross-validation and model regularization, especially when working with limited sample sizes.

To ensure robustness, a 5-fold stratified cross-validation was conducted. Cross-validated performance metrics (Accuracy, Sensitivity, Specificity, and AUC) were computed for both raw and PCA-transformed datasets. Across all models, cross-validation confirmed high stability. Notably, RF trained on raw data achieved the highest AUC ($0.985 \pm 0.022$), followed closely by XGBoost ($0.970 \pm 0.033$) and MLP ($0.968 \pm 0.039$).

The study also explored PCA as a dimensionality reduction strategy. Although PCA was applied strictly on the training data to prevent information leakage, its benefit on model performance was mixed. While it helped reduce collinearity and improve interpretability, models trained on raw features often outperformed those using PCA-transformed features. This can be attributed to the fact that the first three components retained only 53% of the variance, potentially omitting important information.

Our findings are consistent with prior literature that employed ML in addiction detection. For example, Lee et al. [23], used EEG and neuropsychological data for behavioral addiction classification, and Coelho et al.[12] showed moderate sensitivity for clinical tests like CUDIT-R. In contrast, our ML pipeline, using readily available psychometric tools, achieved higher classification performance and better generalization.

Importantly, our study underscores that simple, interpretable models such as LR can perform on par with, or better than, complex models, particularly when paired with appropriate feature engineering and validation strategies. This is especially relevant in clinical practice, where transparency and reproducibility are crucial for model adoption.

However, limitations must be acknowledged. The relatively small and localized sample limits external validity. Additionally, addiction status was treated as a binary label, which oversimplifies the continuum of substance use behavior. Future work should explore multi-class or severity-level prediction, and test the models in broader populations and longitudinal frameworks.

In summary, ML models trained on cognitive and sleep features offer a promising and cost-effective approach to support early detection of cannabis addiction. Their integration into clinical workflows could enhance existing screening strategies, promoting timely intervention and better patient outcomes.

## VI. CONCLUSION

This study demonstrated the potential of machine learning techniques in improving the early detection of cannabis addiction using objective and validated assessment tools such as the Montreal Cognitive Assessment and the Pittsburgh Sleep Quality Index. The predictive models developed, particularly LR and MLP achieved high sensitivity and specificity, outperforming traditional clinical tools such as the DSM-5-based screening. Models trained on raw standardized features performed better than those using PCA-transformed data, indicating that dimensionality reduction was unnecessary in this context. These findings support the potential of ML enhanced screening tools to assist clinicians in the early identification of at-risk individuals based on routine assessments.

Future research should aim to validate these findings on larger and more heterogeneous populations. Incorporating complementary data such as neuroimaging, genetic markers, or behavioral tracking could enhance prediction accuracy. Longitudinal studies are also needed to evaluate the ability of these models to monitor addiction trajectories over time. Finally, embedding explainable AI mechanisms would improve clinical interpretability and foster greater trust in real-world applications.

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# An Obesity Risk Level (ORL) Based on Combination of K-Means and XGboost Algorithms to Predict Childhood Obesity

Ghaidaa Hamed Alharbi, Mohammed Abdulaziz Ikram
Department of Computer Science, Umm Al-Qura University, Makkah, KSA

***Abstract*—Childhood obesity is a common and serious public health problem that requires early prevention measures. Identifying children at risk of obesity is crucial for timely interventions that aim to mitigate these adverse health outcomes. Machine learning (ML) offers powerful tools to predict obesity and related complications using large and diverse data sources. The article uses machine learning (ML) techniques to analyze children's data, focusing on a newly developed variable, the Obesity Risk Level (ORL), which categorizes participants into high, medium, and low risk levels. Two primary models were utilized: the K-Means algorithm for clustering participants based on shared characteristics and XGBoost for predicting the risk level and obesity likelihood. The results showed an overall prediction precision of 88.04%, with high precision, recall, and F1 scores, demonstrating the robustness of the model in identifying obesity risks. This approach provides a data-driven framework to improve health interventions and prevent childhood obesity, providing information that could shape future preventive strategies.**

***Keywords*—Prediction system; Childhood obesity; K-Means; XGBoost; Machine learning**

## I. Introduction

Childhood obesity is a global health issue that affects millions of children and adolescents. According to the World Health Organization, the percentage of overweight and obese children and adolescents aged 5 to 19 years increased from 4% in 1975 to 18% in 2016 [1]. Obesity prevention is an important component of public health efforts, and central to the discipline of obesity prevention is the identification of children at risk. Childhood obesity is an increasingly important issue in healthcare, as it can cause many health problems, such as heart disease, diabetes, metabolic syndrome, mental issues, and early death [2]. Therefore, it is essential to prevent and treat childhood obesity. To achieve this, it is necessary to identify which children are likely to become or are already obese, as well as how they are affected by obesity, including factors such as BMI, weight change, obesity complications, and treatment results. This information can help plan effective and timely interventions that address risk factors and promote healthy habits. However, these factors can vary between different groups, locations, and time periods, so the results of one study cannot be universally applied to another.

In recent years, many studies have used different ML methods to predict childhood obesity and related outcomes, using various data sources, characteristics, and targets [3], [7], [12], [15], [19]. However, the issue of personalized risk prediction has recently become more important. Despite these studies, little importance has been given to personalized obesity risk assessments. Although these studies predict obesity or related outcomes, none of them explicitly focus on predicting an individual's personalized risk of developing obesity, which could help with more targeted prevention strategies. This gap highlights the need for models that go beyond general classifications and provide individualized risk assessments.

To overcome this problem, machine learning (ML) methods have become useful tools that can use large and diverse data sources to build accurate and reliable prediction models for childhood obesity and related outcomes. Recent developments in the field of artificial intelligence and machine learning have led to renewed interest in using data-driven approaches to address these complex health challenges. This study builds on previous research on childhood obesity and contributes to a growing body of work using ML to predict obesity outcomes.

The goal of this study is to use ML algorithms to analyze children's data and to design an intervention that can help children who are at risk of obesity or are already obese to improve their health. In this research, an Obesity Risk Level (ORL) was proposed to classify participants into three levels: high, medium, and low. The goal is to analyze the relationship between individual characteristics and obesity, helping to identify those at higher risk. To achieve this, two models were used: the K-Means algorithm to group participants based on shared traits, and XGBoost to predict risk level and classify likelihood of obesity. The results demonstrated an overall precision of 88.04%, with strong performance in metrics such as precision, recall, and F1 score. These findings validate the effectiveness of the model in making precise predictions, helping to identify targeted preventive efforts and health interventions.

The remainder of the paper is organized into six sections, each focusing on a different aspect of the research. Section II presents a detailed overview of the research background and related work. Section III describes the research methodology, including the K-Means clustering process and the use of XGBoost for predictive modelling. Section IV presents the result of the experiment. The discussion part is presented in Section V. Finally, Section VI concludes with a summary.

## II. Review of the Literature

### A. Related Works

In this review of the literature, current research on childhood obesity and the various methods used to predict and analyze it is explored in depth. A considerable amount of literature has been published on factors that contribute to childhood obesity, including genetics, environmental influences, and lifestyle choices [14], [17], [22-23]. Additionally, advanced machine learning techniques have been employed to estimate obesity levels and predict risk using clinical or behavioral data [4-5].

However, relatively little literature has been published on the application of advanced machine learning techniques specifically tailored for the prediction of childhood obesity. In addition, different predictive modelling techniques, such as logistic regression, decision trees, and artificial neural networks, used by researchers to forecast obesity trends are also examined. By examining the existing research, the objective is to uncover knowledge gaps and deliver insights that may lead to improved strategies for preventing and managing childhood obesity.

Among recent efforts to predict childhood obesity using advanced machine learning techniques, Gupta et al. [6] developed a deep neural network architecture based on recurrent neural networks (RNNs). Their study specifically investigated how temporal patterns in pediatric health data could be leveraged to forecast obesity risk over one, two, and three years intervals. They used RNNs with LSTM (long-short-term memory) cells combined with a separate feedforward network for training their model. They trained the models using a large pediatric electronic health record (EHR) data set. They achieved an AUC of 0.80, 0.93, and 0.92 for a 3-year window at 5, 11, and 18 years. They also compared the recurrent model with other machine learning models for the task of predicting childhood obesity and found the LSTM-based model demonstrates better performance compared to traditional machine learning models that ignore the temporality of the data by aggregating the data.

Similarly, in a separate study by Robert Hammond et al. [10] conducted a study in which they used EHR data to predict obesity at five years of age with an AUC similar to cohort studies. They applied different machine learning algorithms for binary classification and regression tasks. They also created separate models for boys and girls. They discovered that the most important prediction characteristics were the weight of the length z score, the BMI from 19 to 24 months, and the last BMI value before age two in each of the models. The best models achieved an AUC of 81.7% for girls and 76.1% for boys in predicting obesity. Their findings indicate that machine learning methods can use EHR data to predict future childhood obesity and help clinicians and researchers design better interventions, policies, and clinical decisions.

In the study by Xueqin Pang et al. [12] seven machine learning models have been developed to predict childhood obesity between the ages of 2 and 7 years using data from the Electronic Healthcare Record (EHR). Furthermore, these studies relied on machine learning algorithms to assess and predict obesity. Furthermore, Cheong Kim et al. [8] applied GBN-MB along with several other algorithms, such as GBN, LR, DT, SVM, and NN, as part of a proof of concept to analyze public health and simulate future outcomes through What-If analysis. Xiaolu Cheng et al. [9] focused on understanding the relationship between physical activity and weight status, using data from NHANES (2003–2006) and evaluating 11 classification algorithms, including logistic regression, k-NN, RBF, and J48.

Faria Ferdowsy et al. [11] applied nine different ML algorithms, including k-NN, random forest, and logistic regression, to classify obesity levels (high, medium, and low) in a dataset of over 1100 individuals. Each of these studies explored different ML models tailored to their research objectives. Cheong Kim et al. [8] demonstrated that the GBN-MB model produced the best results in simulating health outcomes and guiding public health professionals. Similarly, Xiaolu Cheng et al. [9] found that physical activity was a key predictor of weight status, with machine learning models offering valuable insights into demographic factors such as age, gender, and race/ethnicity.

In summary, the reviewed studies illustrate the diversity of approaches for predicting and estimating obesity, ranging from Bayesian-optimized neural networks to decision trees, Bayesian networks, and deep learning models. Ultimately, while each method has its strengths and limitations, the growing trend is towards utilizing electronic health records, integrating multiple data sources, and developing interpretable models for clinical and public health applications. Looking ahead, the future of obesity prediction research will likely focus on improving the balance between precision, interpretability, and practical applicability, particularly in pediatric and adolescent populations where early intervention is critical.

### B. Machine Learning Models

Machine learning methods, such as Decision Trees, K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Support Vector Machines (SVC), Logistic Regression, Random Forest, AdaBoost, XGBoost, and K-Means, are powerful tools for developing predictive models that help identify factors that contribute to childhood obesity. Although many studies have demonstrated the effectiveness of these models in various healthcare applications, relatively few have focused on their specific use in the prediction of childhood obesity. This gap highlights a critical area for future research.

These models are capable of evaluating complex relationships between variables such as genetics, lifestyle, environmental influences, and diet habits. Numerous studies have demonstrated that machine learning methods are highly efficient in handling large datasets, revealing hidden patterns that traditional statistical methods may overlook. For example, models such as Random Forest and XGBoost have been shown to significantly improve the accuracy of obesity-related predictions. Using these advanced algorithms, researchers aim to identify high-risk groups for childhood obesity, allowing the development of targeted and effective preventive strategies. Furthermore, these models provide deeper insights into how specific factors influence obesity, allowing for more personalized interventions customized to individual needs.

Although much of the current research has focused on improving predictive accuracy, there is a growing emphasis on

ensuring that these models are interpretable and actionable. Making models more understandable will allow healthcare professionals to apply findings in practical ways, improving resource allocation for the prevention and management of obesity in communities. Early identification of risk factors through machine learning has been shown to improve outcomes by enabling timely interventions.

Incorporating data from various sources, such as electronic health records (EHR) and lifestyle surveys, is expected to further improve the ability of these models to predict obesity risks. By analyzing a wide range of factors and sources, machine learning can support the design of more comprehensive and effective strategies to mitigate the increasing rates of childhood obesity.

### C. Obesity Childhood

Childhood obesity is a global health problem characterized by excess body fat that significantly affects both physical and mental well-being. The following are key points regarding childhood obesity.

*1) Definition and measurement:* Childhood obesity is commonly assessed using the body mass index (BMI), a tool used to determine whether a child's weight is appropriate for their age and height [1].

*2) Health risks:* Being obese as a child can cause many health problems, such as heart disease, diabetes, metabolic syndrome, mental problems, and early death [2].

*3) Causes:* Multiple factors contribute to childhood obesity, including poor nutrition, lack of physical activity, genetic predisposition, and environmental influences such as access to healthy food and safe spaces for exercise [20].

*4) Prevention and management:* Addressing childhood obesity requires a holistic approach that incorporates healthy diet changes, increased physical activity, and behavioral modifications. Family involvement and community support are essential to create environments that promote healthy living [21].

### D. Obesity Factors

*1) Genetic:* Genetics plays a crucial role in shaping children's likelihood of developing obesity. Genes that regulate appetite, metabolism, and fat storage increase the risk of obesity, particularly in children with a family history of the disease. Studies have found that somewhere between 25% and 40% of your BMI is actually inherited [17].

*2) Physical activity:* A sedentary lifestyle is widely recognized as one of the key factors strongly associated with the increase in obesity rates. This lifestyle is characterized by prolonged periods of inactivity, such as sitting for long hours while watching television or participating in other screen-based activities. Research has shown that each additional hour spent watching television per day can increase the likelihood of developing obesity by 2% [17]. Over time, these seemingly small increases can accumulate, contributing to significant health risks, as reduced physical activity leads to lower energy expenditure and, consequently, weight gain.

*3) Dietary habits:* There is a strong connection between childhood obesity and eating habits [22]. Choosing nutrients dense foods and maintaining balanced eating patterns are essential to prevent obesity. Proper portion control and reducing high-calorie and low-nutrient foods can significantly reduce the risk of childhood obesity.

*4) Environmental factors:* Children who live in unsafe areas or who do not have access to well lit, safe walking routes have fewer opportunities to be physically active [17]. In interviews conducted by Jenny Veitch et al. [23], the most commonly reported factor affecting where children played was parents' concerns about their child's safety, with 94% of parents expressing this concern. Safety was a crucial factor in parents' decisions about where their children could play. Therefore, the availability of a safe neighborhood was directly related to increased opportunities for children to engage in active free play.

*5) Sleep hours:* Poor sleep and sleep disturbances are associated with weight gain in children. A study by Christopher Magee et al. [24] suggests that poor sleep may be a contributing factor to childhood obesity.

*6) Socioeconomic Status (SES):* Robert Rogers [25] stated that their findings suggest that low SES plays a more significant role in the nation's childhood obesity epidemic than any other demographic factors.

Childhood obesity is a multifaceted problem influenced by a combination of genetic factors, environmental conditions, and lifestyle choices. Genetic factors may contribute to childhood obesity, but environmental factors, such as access to healthy foods and safe recreational spaces, and lifestyle habits, such as eating patterns and levels of physical activity, are equally important. To effectively address this complex problem, parents must provide ongoing emotional support to their children, regardless of their weight. Parents must instead focus on creating a supportive and positive home environment that encourages everyone to eat healthy and be physically active regularly. By promoting these habits and spreading them throughout the family, parents can help reduce the risk of obesity and support children in achieving and maintaining a healthy weight.

## III. Methodology

In this part of the article, details of the methods used to analyze and model childhood obesity are provided. The explanation begins with the data collection process, including the sources and characteristics of the dataset used. Next, the applied methodologies are described, starting with K-Means clustering to group data based on similarities, followed by XGBoost for predictive modelling. The section also covers the tools and software utilized and addresses any technical challenges encountered during implementation. Finally, the evaluation metrics used to assess model performance are discussed. This methodology provides a comprehensive approach to understanding and predicting childhood obesity based on the data analyzed.

### A. Dataset

The study is based on a comprehensive dataset gathered by a university [13], reflecting a wide range of student profiles from various schools. In collaboration with school administrations, surveys collected data on demographic characteristics and anthropometric measurements. It is noteworthy that a subset of these data, specifically involving 411 identified students with 15 variables, will be utilized in the study. This carefully selected dataset allows for a detailed analysis, contributing to a comprehensive understanding of the educational context and the relationships between various factors. Table I outlines the features used in this study along with their detailed descriptions. Each feature was selected based on its relevance and contribution to the objectives of the research. The descriptions provided help to clarify the significance of these variables, offering a clearer understanding of how they interact and influence the overall analysis. When exploring these characteristics, deeper insights can be gained into the factors that shape the outcomes observed in the data, making them essential for drawing informed conclusions from the study.

TABLE I. DATASET FEATURES

| Parameter | Description |
|---|---|
| St_Height | Height of the student in centimeters |
| St_Weight | Weight of the student in kilograms |
| M_Weight | Mother's weight in kilograms |
| M_Height | Mother's height in centimeters |
| F_Weight | Father's weight in kilograms |
| F_Height | Father's height in Centimeters |
| Appearance_self | Body image perception, rated 1 to 5 |
| Body_pride | Body self-esteem, rated 1 to 5 |
| Neighborhood_jog_safe | Safety of jogging in the neighborhood, rated 1 to 5 |
| Neighborhood_bike_safe | Safety of cycling in the neighborhood, rated 1 to 5 |
| Family_income | Family income level, rated 1 to 8 |
| Gender | Student's gender |
| Birthday | Student's date of birth |
| Obese_Student | Obesity classification (binary) |
| S_BMI | Student's BMI category |

These variables, which cover a diverse range of information and survey responses, serve as the foundation for the study's analysis. They offer a comprehensive snapshot of the students' profiles, facilitating a nuanced examination of the factors under scrutiny.

### B. Prediction System

First: K-means algorithm

The K-Means algorithm is a common technique in machine learning to group data into groups (clusters) so that the data within each group are as similar as possible [16].

K-Means is a clustering algorithm that partitions a dataset into $K$ distinct clusters. Here is a simplified explanation of the steps.

*1) Specify the number of clusters($k$):* Determine the number of clusters into which you want to divide the data. This number is called $k$.

*2) Initialise the cluster centre:* Randomly select $k$ points from the data as the initial cluster center.

*3) Assign data points to clusters:* For each data point, calculate the distance between it and the center of each cluster. Assign points to the nearest cluster center.

*4) Update cluster centres:* After assigning points to clusters, recalculate the centers of each cluster based on the points assigned to each cluster.

*5) Repeat:* Repeat steps 3 and 4 until the center is stable and does not change significantly.

*6) Complete:* When the center is stable, the algorithm is complete and the clusters are formed.

Objective Function:

$$Minimize \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2 \quad (1)$$

where,

- $k$ is the number of clusters.
- $C_i$ represents the $i$-it cluster.
- $x$ is a data point.
- $\mu i$ is the centroid of the cluster $C_i$

As shown in Fig. 1, the plot on the left shows the data before applying K-Means, where the points are ungrouped and displayed in uniform color, indicating that no clustering has been applied. In contrast, the plot on the right shows the data after K-Means clustering, where the data points are grouped into distinct clusters, each represented by a different color. The red stars indicate the centroids of each cluster, which are the central points of each group.

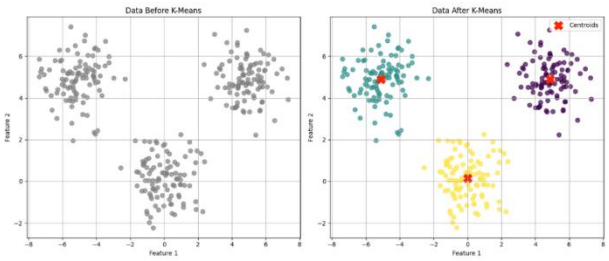


Fig. 1. Data visualisation before and after applying the k-means clustering algorithm.

### C. Implementation

The K-Means algorithm has been successfully applied to the data with K=80. A new column named "Cluster" has been added, showing which cluster each student belongs to. Defining K=80; this means that we want to divide the students into 80 groups. Each group represents students with similar characteristics according to the specified features.

*1) Choose the columns for clustering:* To perform K-Means, we have used the columns of the data because they

reflect important factors such as parents' weight and height, personal behavior, environment, and family income.

*2) Scaling:* Since the columns contain values of different scales (such as family income vs. height), we scaled them using Standard Scaler to ensure that each feature contributes equally. Scaling means converting the values to a uniform range so that each column has a mean of 0 and a standard deviation of 1.

*3) Initialise clusters:* The initial centers are chosen randomly for 80 clusters.

Assign points to clusters: For each student, the distance between their data (such as mother's weight, father's height, family income, etc.) and each of the cluster centers is calculated.

The student is assigned to the nearest cluster.

*1) Update cluster centres:* A new center is calculated for each cluster based on the average values of all students within it.

Iteration: The previous two steps are repeated until the clusters stabilize (i.e., there is no significant change in the assignment of students).

*a) Output (group column)*

A new column named "Cluster" has been added to the data. This column contains the cluster number to which each student belongs (from 0 to 79, since we set K=80).

*b) Example of results*

- Student 1: Data: Mother's weight 52.4, Mother's height 157, Father's weight 82... etc.
- Assigned to group 78.
- Student 2: Data: Mother's weight 55, Mother's height 172, Father's weight 90, etc.

Assigned to group 3.

Second: XGBoost

XGBoost is a powerful and efficient tool to boost tree-based models. Moreover, it has been improved to become highly scalable, which is why it is widely used in various machine learning applications [18]. In fact, XGBoost stands out as a highly effective and popular algorithm for this purpose [18]. Specifically, it improves on traditional tree boosting by building multiple models sequentially, where each model corrects the errors of its predecessors to enhance overall performance. XGBoost addresses these issues with several key innovations. First, it incorporates a regularization term into the objective function to reduce model complexity and prevent overfitting. Additionally, it efficiently handles missing values and sparse data, which is crucial for working with large and incomplete datasets. In terms of speed and scalability, XGBoost employs advanced parallelization techniques, processing feature blocks in parallel and distributing tasks across multiple processors. Moreover, it optimizes memory access patterns to reduce unnecessary operations, thereby enhancing performance with massive datasets. Furthermore, XGBoost can handle datasets larger than memory capacity by leveraging external storage efficiently. As a result, the strengths of XGBoost include its impressive speed and efficiency, achieved through effective parallelization and optimized memory usage. In addition, its accuracy and effectiveness are enhanced by regularization and second-order optimization techniques.

Consequently, XGBoost is widely used across various fields due to its ability to manage large and sparse data effectively. In summary, XGBoost is a powerful and scalable tool for boosting tree-based models, offering significant improvements in performance and applicability in machine learning. To conclude, XGBoost (Extreme Gradient Boosting) is a powerful machine learning algorithm designed for efficient and scalable decision tree boosting. Specifically, it improves traditional gradient boosting by incorporating advanced techniques such as regularization to prevent overfitting, parallel computation for speed, and handling of sparse data for improved performance on large and complex datasets.

*c) XGBoost Equation and Explanation:* The XGBoost equation is based on the gradient boosting technique with several optimizations to make it more efficient and effective. The main idea is to gradually create decision trees that correct the errors made by previous trees, and these corrections are combined to form the final prediction.

*d) XGBoost Equation:* Let us assume that there are $K$ decision trees. The prediction of the model for any sample $x\_i$ is calculated as follows:

$$\hat{y}_i = \sum f_k(x_i) \quad (2)$$

where,

- $\hat{y}_i$ is the final prediction for the sample $x_i$.
- $f_k(x_i)$ is the function representing the $k$ -th decision tree, which produces a prediction for sample $x_i$.
- $K$ is the number of trees.

*e) Objective Function:* The model is optimized by minimizing the objective function, which consists of two parts:

Loss function: Measures the difference between the predictions and the actual values. The commonly used loss function is the squared error for regression problems or the logistic loss for classification problems.

$$L(\hat{y}, y) = \sum l(y_i, \hat{y}_i) \quad (3)$$

where $l(y_i, \hat{y}_i)$ is the loss function that measures the difference between the prediction $\hat{y}\_i$ and the actual value $y\_i$ for sample $i$.

Regularization term: Helps to control the complexity of the model and reduce overfitting by penalizing the number of trees and their complexity.

$$\Omega(f) = \gamma T + (1/2)\,\lambda \sum w_j \quad (4)$$

where,

$\gamma$ is the parameter that penalizes adding new nodes to the tree.

$T$ is the number of nodes in the tree.

$\lambda$ is the regularization parameter that controls the size of the weights associated with the nodes.

$w_j$ is the weight associated with each node in the tree.

*f)* Final Objective Function:

$$Objective = \sum l(y_i, \hat{y}_i) + \Sigma \Omega(f_k) \quad (5)$$

where,

The first part $\Sigma\, l(y_i, \hat{y}_i)$ represents the total loss over all the samples. The second part $\Sigma\, \Omega(f_k)$ is the sum of the regularization terms for each tree, limiting the model's complexity.

*g) How XGBoost Optimizes:* XGBoost builds trees progressively, updating predictions at each step. This is done using Gradient Descent, where the first and second derivatives of the loss function are computed to optimize the model gradually:

First Derivative (Gradient): Represents the rate of change of the loss with respect to the prediction.

$$g\_i = \partial L(y_i, \hat{y}_i) / \partial \hat{y}_i \quad (6)$$

Second derivative (Hessian): Represents the rate of change of the first derivative (used to speed up the gradient calculation).

$$h\_i = \partial^2 L(y_i, \hat{y}_i) / \partial \hat{y}_{i^2} \quad (7)$$

*h) Problem Setup:* Aim to classify whether a student is obese ("obese student" = 1) using various features.

1. Input data:

The sample contains the following columns:

Features: q5, q6, q11, q12, s_q7_1, s_q7_3, s_q8_1, s_q8_2, q16, gender, cluster.

Target: obese_student

2. Objective of prediction:

The goal is to determine whether a student is obese (obese_student = 1) or not (obese_student = 0) based on the input features.

3. How the prediction works:

The XGBoost model predicts each feature taking it as input to the model. Based on the relationships discovered during training, the model calculates a probability score to classify the student as "obese" or "non-obese."

4. Example:

Features:

q5 = 80.0, q6 = 165.0, q11 = 55.0, q12 = 175.0, s_q7_1 = 4, s_q7_3 = 3, s_q8_1 = 4, s_q8_2 = 4, q16 = 3, gender = 0, Cluster = 9

Steps:

After combining tree contributions, the final score might be $\hat{y} = -0.3$.

Applying the Sigmoid function:

$$P(obese) = \frac{1}{1 + e^{-(-0.3)}} \approx 0.43$$

Since $P(obese) < 0.5$, the model predicts obese_student = 0 (non-obese).

### D. Integrating K-Means and XGBoost

Combining K-Means with XGBoost presents a robust framework for anomaly detection in logarithmic data sets, leading to accurate and fast results with fewer errors [26]. It leverages the strengths of both algorithms to improve prediction accuracy and model performance.

*1) Purpose of Combining K-Means and XGBoost:* One effective method of combining K-Means and XGBoost is to use K-Means as a preprocessing step. In this approach, K-Means clusters the data into groups based on shared characteristics, allowing for the identification of patterns in the data. These cluster labels are then used as additional features for the XGBoost model, improving its ability to make predictions. By integrating clustering before applying XGBoost, the model can capture more nuanced relationships between variables, leading to more accurate predictions, particularly in complex datasets like those related to childhood obesity.

*2) Methods to Combine K-Means and XGBoost:* K-Means Clustering: Initially, K-Means is applied to group data into distinct clusters based on the similarity of data points. The primary objective of K-Means is to partition the data set into cohesive clusters where the data points within each cluster are similar and close to each other.

Utilizing Cluster Information as a Feature: Once K-Means has assigned clusters, the cluster label (the number assigned to each data point's cluster) is incorporated as an additional feature in the dataset. This enhanced data set, which now contains cluster information, is then fed into the XGBoost model. The added cluster labels provide the model with valuable insights about the underlying structure of the data, potentially improving the model's predictive accuracy.

XGBoost for Prediction: After enriching the dataset with cluster information, XGBoost is used for either classification or regression tasks. As a powerful and widely adopted tree-boosting algorithm, XGBoost can utilize the cluster feature to better capture patterns and relationships in the data, leading to more precise predictions.

This approach of combining K-Means clustering with XGBoost preprocessing helps improve model performance by adding a layer of cluster-based structure to the data.

As shown in Fig. 2, the process begins with applying K- Means clustering to the raw data, generating cluster labels. These labels are then combined with the original data, creating an enhanced dataset. Finally, the enhanced dataset is used as input for the XGBoost model to produce the prediction results.

Flow diagram:

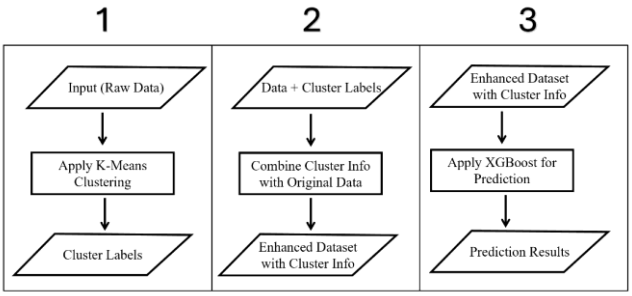


Fig. 2. Integration of K-Means clustering and XGBoost for predictive modelling.

*3) Benefits and Challenges*

*a) Benefits:* Improved accuracy: By clustering data first, XGBoost can make more accurate predictions within each group.

Discovering Hidden Patterns: Clustering can reveal hidden patterns that were not visible in the raw data, allowing XGBoost to make better-informed predictions.

*b) Challenges:* Choosing the right number of clusters: Deciding how many clusters to use in K-Means can be difficult and may require testing different values to find the best result.

Increased computational complexity: Combining K-Means and XGBoost can be computationally expensive, especially for large datasets, as it requires running both clustering and multiple model training processes.

Combining K-Means with XGBoost is an effective strategy to improve predictions in complex and heterogeneous data sets. K-Means helps to organise the data and uncover hidden patterns, while XGBoost uses this information to make more accurate predictions. This approach is particularly useful in domains such as marketing, healthcare, and finance, where segmenting data can lead to more targeted and effective models.

## E. Clustering with K-Means

K-Means clustering was employed to group the data into 80 clusters. During the experimentation phase, several different values for the number of clusters to determine the optimal configuration for the data. Through this process, it became clear that 80 clusters offered the best balance between maintaining a manageable level of complexity and achieving a high level of classification accuracy. Therefore, after careful consideration and testing, 80 clusters were chosen as the ideal number, as they effectively captured the nuances in the data while optimizing the overall performance of the model. This thorough approach is one of the main reasons for settling on 80 clusters. Each cluster was analyzed for the percentage of obese students, leading to the classification of clusters into risk levels (high, medium, low). The data was then annotated with these risk levels.

Risk Level Classification (Obesity Risk Level (ORL)):

$$ORL \begin{cases} \text{High Risk} & \text{if Percentage of Obese Students} \geq 70\% \\ \text{Medium Risk} & \text{if } 40\% \leq \text{Percentage of Obese Students} < 70\% \\ \text{Low Risk} & \text{if Percentage of Obese Students} < 40\% \end{cases}$$

The classification of risk level based on the percentage of obese students is designed to reflect the severity of the health issue and highlight the influence of surrounding factors on obesity rates. Here is why it is divided in this way:

High Risk (70%): When the percentage of obese students is very high (greater than or equal to 70%), it indicates a severe issue, suggesting that the surrounding factors—such as those studied in this research, including parental weight and height, neighborhood safety, monthly income, and psychological factors—have a significant impact on individuals, potentially leading to a higher likelihood of obesity. In this case, these factors seem to play a major role in shaping the health outcomes of students.

Medium Risk ($40\% \leq x < 70\%$): At this level, the obesity rate is moderate, indicating that surrounding factors still have a considerable influence on students. This means that while not as severe as in the "high-risk" category, these environmental, social, and psychological factors still contribute to obesity, but perhaps to a lesser extent. Therefore, it is essential to address these factors to prevent further escalation.

Low Risk (<40%): When the percentage of obese students is below 40%, it suggests that the impact of surrounding factors is relatively less significant in leading to obesity. However, preventive action is still crucial, as factors such as parental characteristics, neighborhood conditions, and psychological well-being can still play a role in maintaining or reducing obesity rates over time.

To conclude, the higher the percentage of obese children in each risk category, the greater the influence of surrounding factors, such as those explored in this study, on individuals, potentially leading to obesity. This classification underscores the need for targeted interventions addressing these factors to mitigate obesity rates at different risk levels.

## F. Modelling with XGBoost

After that, the XGBoost algorithm is applied to train the model in the dataset. XGBoost is one of the most powerful machine learning algorithms and is based on the Gradient Boosting technique to progressively build multiple trees. Each tree corrects the errors made by the previous ones and, through this iterative process, the accuracy of the predictions improves with every new tree added to the model.

## G. Steps to Analyse and Classify Student Obesity Risk

This section provides a structured overview of the process used to analyze student data to identify and classify risk levels for obesity. The workflow includes data loading, preprocessing, exploratory analysis, data balancing, and the application of the K-Means clustering algorithm, culminating in user-specific obesity risk assessment.

*1)* These steps cover the entire process from data loading to user-specific risk assessment.

*a)* Data Loading and Exploration:

- Load Data: Import data from a CSV file and examine the structure, including data types and missing values.

- Exploration: Review the dataset to understand its composition and identify potential issues such as missing or incorrect values.

*b)* Data Processing and Transformation:

- Text to Numeric Conversion: Convert text data into a numerical format for easier processing.
- Data cleaning: Remove unnecessary data points and create new relevant features.

*c)* Exploratory Analysis:

- Correlation Analysis: Compute and display the correlation matrix between features to identify relationships between variables.
- Outlier Detection: Use the interquartile range (IQR) method to detect outliers in numerical features.
- Box plot: Visualize the distribution of numerical data and identify outliers.
- Bar plot: Plot categorical data such as gender and the presence of obesity to understand distributions.

*d)* Data Balancing:

- Apply SMOTE (Synthetic Minority Over-sampling Technique): Balance the dataset by increasing the number of samples in underrepresented categories.
- Post-SMOTE Analysis: Display the dataset distribution after applying SMOTE to ensure balance.

*e)* Clustering of K-Means:

- Cluster Formation: Apply the K-Means algorithm with 80 clusters to the weighted data of 694 samples. Through experimentation, 80 was determined to be the optimal number of clusters.
- Obesity Percentage Calculation: Calculate the percentage of obese students within each cluster and determine the corresponding risk levels.

*f)* Report and Analyze Results:

- Summary: Provide a detailed summary of the number of obese students and their percentages at different risk levels.
- Cluster Classification: Classify the clusters into predefined risk levels (High, Medium, Low) and display the data accordingly.

*g)* User-Specific Risk Assessment:

- Data input: Collect input data from the user.
- Risk Level Determination: Based on user input, classify your risk level of obesity using the K-Means model.

The objective of this process is to thoroughly analyze student data to uncover obesity patterns and identify risk levels. This involves examining various factors, such as birth date, sex, and other characteristics. By applying K-Means clustering, students are grouped based on similar characteristics, allowing us to better understand obesity trends and provide actionable insights for intervention.

*2) Apply XGBoost:* Once the data have been clustered, the next step is to develop a predictive model using the XGBoost algorithm. XGBoost is known for its high performance, making it ideal for handling large datasets and complex relationships.

*a) Data Preparation:*

Input data: Use the clustered data from the K-Means algorithm. The data, now organised into clusters, helps to reveal deeper relationships and structures.

*b) Model Training:*

Train XGBoost: Train the XGBoost model on the clustered dataset, feeding the input features and their corresponding target labels to learn patterns and predict results.

*c) Hyperparameter Tuning:*

Optimise model: Improve the performance of the model by fine-tuning key hyperparameters such as the learning rate, maximum depth, and number of estimators. This can be done using methods such as grid search or random search.

*d) Model Evaluation:*

Performance metrics: Evaluate the model using metrics such as precision, precision, recall, and F1 score to determine how well the model predicts obesity risk levels.

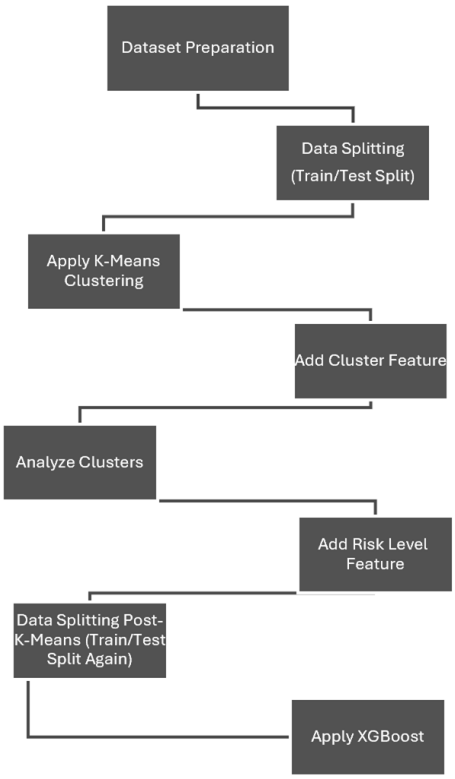


Fig. 3. Flowchart of the analysis process using K-Means and XGBoost.

As shown in Fig. 3, the process of applying K-Means clustering followed by XGBoost in the analysis of obesity risk. The flowchart highlights key steps such as data preparation, clustering, risk level classification, and finally, the use of XGBoost to build a robust predictive model. The diagram provides a clear view of how clustering is integrated with predictive modelling to assess the risks of obesity in students.

## IV. Experiments and Results

The primary objective of this analysis was to determine whether it is possible to predict childhood obesity based on environmental factors. The study aims to explore the relationship between a child's environment and the probability of obesity by applying machine learning models such as K- Means for clustering and XGBoost for predictive modelling.

### A. Overview of the Dataset

The dataset used for this study comprised 411 identified students, including 15 key variables related to both the child's physical characteristics and environmental factors. After applying SMOTE to balance the dataset, the number of samples increased to 694. The dataset includes the following key variables:

Mother's Weight (M_Weight), Mother's Height (M_Height), Father's Weight (F_Weight), Father's Height (F_Height), Appearance self-assessment (appearance_self), Body pride (body_pride), Neighborhood safety for jogging (neighborhood_jog_safe), Neighborhood safety for biking (neighborhood_bike_safe), Family's monthly income (family_income), Gender, Birthday, Obese Student (Obese_Student)

### B. Applied Models

The analysis involved the use of two main models:

*1)* K-Means for clustering students based on similarities in their features.

*2)* XGBoost for building predictive models based on the generated clusters.

### C. Performance Metrics

The XGBoost model was evaluated based on several performance metrics that provided insight into its effectiveness in predicting obesity risk. The model achieved the following metrics: As seen in Table II, the performance metrics for the obesity classification model are outlined, including Precision, Recall, F1-score, and Support for both non-obese (Class 0.0) and obese (Class 1.0) categories. These metrics provide a detailed evaluation of the model's ability to accurately classify obesity.

TABLE II. Performance Metrics for Obesity Classification Model

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| 0 (Not Obese) | 0.93 | 0.85 | 0.89 | 118 |
| 1 (Obese) | 0.82 | 0.92 | 0.87 | 91 |

As seen in Table III, the macro and weighted average performance metrics of the obesity classification model are presented. The model achieves a macro average precision of 0.88, recall of 0.89, and an F1-score of 0.88. Similarly, the weighted averages show strong performance, with precision at 0.89, recall at 0.88, and an F1-score of 0.88. The overall accuracy of the model is 88.04%, reflecting its reliability in predicting obesity across the data set.

These results indicate strong performance across all metrics, validating the model's ability to accurately predict childhood obesity based on environmental factors.

TABLE III. Overall Performance Metrics for Obesity Classification Model

| Metric | Value |
|---|---|
| Macro Average Precision | 0.88 |
| Macro Average Recall | 0.89 |
| Macro Average F1-score | 0.88 |
| Weighted Average Precision | 0.89 |
| Weighted Average Recall | 0.88 |
| Weighted Average F1-score | 0.88 |
| Overall Accuracy | 88.04% |

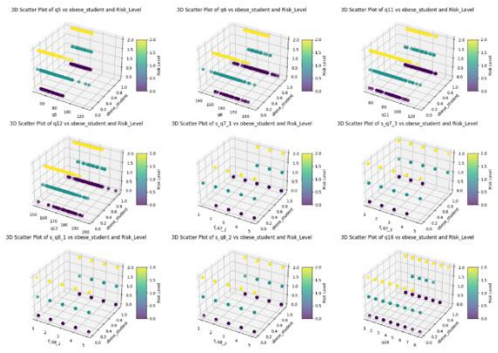

Fig. 4. 3D scatter plots showing the relationship between various characteristics, obesity, and risk levels.

The results of the analysis are supported by 3D scatter plots as seen in the Fig. 4. These graphs visually demonstrate the relationship between different characteristics such as parental weight, neighborhood safety, and child's risk of obesity. The color-coded risk levels (purple, teal, yellow) highlight distinct clusters where, environmental factors align with the likelihood of obesity. This representation makes it easier to identify how certain characteristics influence the risk levels.

### D. Risk Level Categorisation

As seen in Table IV, the clusters are categorized by their risk levels based on the proportion of obese individuals in each group. The table includes the cluster number, the number of obese individuals, the percentage of obese individuals, and the associated risk level. Clusters with a higher percentage of obesity are classified as high-risk, while those with lower percentages are categorized as 'medium risk' or 'low risk.' This classification helps identify obesity prevalence within different clusters, providing insight into the varying levels of risk across the groups.

This section provides a detailed breakdown of obesity rates among children, classified into high-, medium-, and low-risk clusters. Each row in the table represents a cluster, detailing the number of obese children, the percentage of obese children within that cluster, and the associated risk level.

*1) High risk:* Clusters in the high-risk category exhibit a significantly high percentage of obese children. Key points include:

Clusters 18, 62, and 41 show a 100% obesity rate, indicating that all children in these clusters are classified as obese. Clusters 14 and 25 demonstrate high obesity rates of 92.86% and 84.62%,

respectively. The lowest percentage within this category is 70% (Cluster 40), which still indicates a substantial proportion of obese children. These findings suggest that in high-risk groups, most children are obese, with some groups having all children classified as obese.

TABLE IV. ALL RISK LEVELS CLUSTERS

| Cluster | Number_of_Obese | Percentage_of_Obese | Risk_Level |
|---|---|---|---|
| 18 | 12 | 100 | high risk |
| 62 | 3 | 100 | high risk |
| 41 | 5 | 100 | high risk |
| 35 | 6 | 100 | high risk |
| 14 | 13 | 92.86 | high risk |
| … | … | … | … |
| 22 | 10 | 66.67 | medium risk |
| 15 | 6 | 66.67 | medium risk |
| 78 | 4 | 66.67 | medium risk |
| 7 | 8 | 66.67 | medium risk |
| … | … | … | … |
| 58 | 1 | 12.5 | low risk |
| 21 | 0 | 0 | low risk |
| 67 | 0 | 0 | low risk |
| 24 | 0 | 0 | low risk |
| … | … | … | … |

*2) Medium risk:* Clusters in the medium-risk category have lower obesity rates compared to high-risk clusters, but the rates are still significant:

Clusters 22, 15, and 78 show an obesity rate of 66.67%, which means that approximately two-thirds of the children in these clusters are obese. Clusters such as 68 and 65 show obesity rates of around 64.29% and 62.50%, respectively. The lowest obesity rate within this category is 42.86% (Clusters 13, 77, and 27).

This category indicates a moderate level of obesity, with a substantial proportion of children classified as obese, though less prevalent than in the high-risk clusters.

*3) Low Risk:* In the low-risk category, obesity rates are significantly lower:

Clusters such as 45, 16, and 73 show a 33.33% obesity rate, which means that only one-third of the children in these clusters are obese. Some clusters, such as Cluster 79, have an obesity rate as low as 15.38%. Several clusters (eg, clusters 21, 67, and 24) show a 0% obesity rate, indicating that there are no obese children in these clusters. These clusters display minimal levels of obesity, and many clusters having no children classified as obese at all.

### *E. Obesity by Risk Levels*

As seen in Table V, the summary of obesity by risk levels provides an overview of the number of obese individuals, total individuals, and the percentage of obese individuals within each risk category. The high-risk group exhibits the highest percentage of obese individuals, at 80.63%, followed by the medium-risk group at 56.16%, and the low-risk group at 12.18%.

TABLE V. OBESITY SUMMARY BY RISK LEVEL

| Risk_Level | Number_of_Obese | Total_Number | Percentage_of_Obese |
|---|---|---|---|
| high-risk | 204 | 253 | 80.63 |
| medium risk | 114 | 203 | 56.16 |
| low risk | 29 | 238 | 12.18 |

This summary highlights the varying prevalence of obesity at different risk levels, with obesity rates much higher in high-risk groups compared to medium and low-risk groups.

The results confirmed the initial hypothesis that a child's surrounding environment plays a significant role in their likelihood of becoming obese. Factors such as parental weight, neighborhood safety, and socioeconomic status (as indicated by family income) were found to be closely related to obesity risk levels. This finding is consistent with previous research, confirming the importance of these environmental influences on childhood obesity.

The results were generally consistent with previous studies, which also emphasized the role of environmental and familial factors in determining the risk of obesity. However, the integration of machine learning techniques, such as K-Means and XGBoost, provided a more refined predictive model with high precision in this study.

## V. DISCUSSION

The purpose of this chapter is to interpret and discuss the results obtained from the analysis of childhood obesity based on environmental factors. By applying machine learning techniques such as K-Means for clustering and XGBoost for predictive modelling, this study aimed to uncover patterns and relationships between various factors that influence childhood obesity. The discussion section will evaluate the performance of these models, explore the significance of key findings, and highlight areas for further improvement and future research.

### *A. Model Performance*

The models showed strong performance, especially in terms of precision, recall, and F1 scores. The XGBoost model, in particular, was highly effective in predicting obesity risks, achieving an overall accuracy of 88.04%. These findings align with existing research, reinforcing the efficacy of machine learning techniques in predicting childhood obesity based on environmental factors.

### *B. Insights from the Study*

The experiment confirmed that various factors, such as parental weight, neighborhood safety, and family income, significantly impact childhood obesity. The models provided valuable information on these relationships. However, there are other important factors, such as duration of sleep, medical conditions, and diet patterns that could further refine the predictions of obesity if included in future research. Despite

promising results, including an accuracy of 88.04%, it is important to consider that there are other factors that influence obesity that were not included in this study. For example, factors such as sleep duration, medical conditions, and eating patterns may play a significant role in determining the risk of obesity among children. These factors could have substantial impacts on the results we obtained and may contribute to improving accuracy if considered in future models. Therefore, it is recommended that future research incorporates a broader range of relevant factors and variables, including dietary patterns, to provide a more comprehensive and accurate assessment of the risk of obesity. Additionally, including more diverse data can help improve model performance and offer deeper insights into the factors that influence obesity.

### C. Recommendations for Future Research

Future research should incorporate a broader range of variables, including diet patterns, sleep habits, and medical conditions, to provide a more comprehensive assessment of the risk of obesity. Furthermore, collecting more diverse data could enhance model performance and provide deeper insights into the factors influencing childhood obesity.

## VI. Summary and Key Findings

### A. Study Approach and Methodology

The research addressed the challenges of childhood obesity using machine learning models, specifically XGBoost for prediction and K-Means Clustering to categorize students based on risk levels. The study began with an extensive review of the literature to understand the current state of research in this field, followed by a comparison of different machine learning approaches. This provided the foundation for selecting and implementing the models that were ultimately used.

### B. Results

Through the application of K-Means Clustering, students were classified into different groups based on their risk of obesity. This clustering method offered valuable information on how various factors, such as socioeconomic status, parental characteristics, and neighborhood conditions, influence a child's likelihood of developing obesity. The clusters created a framework that allowed for a deeper analysis of the risk levels.

Once the clusters were established, XGBoost was applied to predict the risk of obesity with high precision. The model achieved an accuracy of 88.04%, demonstrating its effectiveness in handling the dataset and providing reliable predictions for childhood obesity based on the characteristics extracted from the clustering process. The combination of these techniques proved to be a powerful approach for predictive modelling in this domain.

### C. Broader Implications

These findings highlight the potential of machine learning techniques to advance our understanding of childhood obesity. The success of XGBoost in predicting risk of obesity offers a strong foundation for further research and development. In particular, these methods could be refined to support early interventions, potentially reducing the prevalence of childhood obesity by targeting high-risk groups more effectively.

### D. Conclusion

In summary, this study provides a compelling case for the application of machine learning in health-related fields, specifically in understanding and predicting childhood obesity. The results achieved, especially the accuracy of classification and prediction, suggest that machine learning can play a vital role in future research and public health interventions aimed at combating childhood obesity. Future studies can build on this by incorporating more variables or experimenting with alternative algorithms to improve prediction accuracy and develop targeted intervention solutions.

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# Industry 4.0 for SMEs: Exploring Operationalization Barriers and Smart Manufacturing with UKSSL and APO Optimization

Meeravali Shaik[1], Piyush Kumar Pareek[2]
Research Scholar, Nitte Meenakshi Institute of Technology, Visvesvaraya Technological University, Belagavi-590018, India
Assistant Professor, Sreenidhi Institute of Science and Technology, Ghatkesar, Hyderabad-501301[1]
Research Supervisor, Nitte Meenakshi Institute of Technology, Visvesvaraya Technological University, Belagavi-590018[2]

***Abstract*—The research aimed to find out why SMEs have a hard time adopting smart manufacturing, what makes smart manufacturing operational, and if only large companies can afford to take advantage of technological opportunities. It used a knowledge-based semi-supervised framework named Unsupervised Knowledge-based Multi-Layer Perceptron (UKMLP), which has two parts: a contrast learning algorithm that takes the unlabeled dataset and uses it to extract feature representations, and a UKMLP that uses that representation to classify the input data using the limited labelled dataset. Next, an artificial protozoa optimizer (APO) makes the necessary adjustments. This research is based on the hypothesis that large companies may be able to exploit Small and Medium-sized Enterprises (SMEs) to their detriment in cyber-physical production systems, thus cutting them out of the market. Secondary data analysis, which involved evaluating and analyzing data that had already been collected, was crucial in accomplishing the research purpose. Since big companies are usually the center of attention in these discussions, the necessity to delve into this subject stems from the reality that SMEs have a higher research need. The results confirmed the importance of Industry 4.00 in industrial production, particularly with regard to the smart process planning offered by algorithms for virtual simulation and deep learning. The report also covered the various connection choices available to SMEs in order to improve business productivity through the use of autonomous robotic technology and machine intelligence. This research suggests that a substantial value-added opportunity may lie in the way Industry 4.0 interacts with the economic organization of companies.**

***Keywords*—European small and medium-sized enterprises; artificial protozoa optimizer; knowledge-based semi-supervised framework; contrastive learning algorithm; smart manufacturing***

## I. INTRODUCTION

Because data and the interactions among data cases reveal insights into software and service quality, as well as the dynamics of software creation and evolution, data plays a crucial role in contemporary software development [1-2]. There is a treasure trove of information regarding the development and evolution of a project in Software Engineering (SE) data, including code bases, changes, mailing lists, forum discussion, and bug/issue reports [3]. Automated SE methods and tools have come a long way since their inception, but most of them have concentrated on automating the creation, storage, and management of data that is specific to a single SE task, rather than helping with human experience-based decision-making or increasing productivity across all SE tasks [4]. The aforementioned methodologies and tools for software project decision-making, particularly in the face of uncertainty and that are unable to disclose the hidden linkages among different types of data or the data's deep semantics [5]. Thanks to the advancements in Machine Learning (ML) and Deep Learning (DL) algorithms, ML/DL models can now be trained to systematically evaluate and integrate data from big data software repositories, as to find patterns and new information clusters [6-7]. This paves the way for more thorough and organized information and decision-making frameworks [9] by improving comprehension of the data's deep semantics and interconnections via the use of statistical and probabilistic procedures [8]. Insightful and useful information regarding software systems and projects can be automatically uncovered by ML/DL approaches by analyzing and crosslinking the abundant data found in software repositories, something that cannot be accomplished just by practitioners' intuition and expertise [10]. The use of ML approaches in the automation of SE processes has also been driven by the exponential growth in the volume and difficulty of SE data.

The widespread use of ML/DL for data representation and analysis stems from the fact that many SE problems can be expressed as data analysis (learning) tasks [11]. These tasks include classification, ranking, regression, and generation, where the aims are to classify data instances into predefined categories, induce rankings over data instances, assign real values to data instances, and generate (usually brief) natural language descriptions as outputs [12–13]. As an example, it is natural to cast binary defect prediction as a classification job. This task involves predicting whether new instances of code regions (such as files, modifications, and methods) include faults. Ranking tasks can be applied to software crowdsourcing activities such as code search, defect localization, bug assignment, pull requests, requirements, reports, test case prioritization, and recommendations [14]. Software engineering (SE) researchers also use continuous data with regression models to approximation (1) software development effort [15], (2) software defect count and bug fixing time, (3) configurable software performance, (4) energy consumption, and (5) software reliability, a conditional probability problem. As a last step, certain activities have been reformed as generation tasks. One of them is code summarization, which

involves providing a high-level, plain language description of the code. Another is the development of code artifacts, such as code comments.

To get the feature map out of datasets without labels, to use a contrastive learning model here [30]. In the next step, to build a model besides train it with a small dataset of labels. When tested on several classification datasets, the proposed framework UKSSL outperforms other state-of-the-art algorithms while utilizing a smaller dataset. In order to enhance the classification accuracy, the study work employs the APO model to refine the parameters of the proposed model. Here is a rundown of the remaining research: Section II lists relevant literature; Section III gives a brief overview of the proposed technique; Section IV analyses the results; and Section V attractions conclusions.

## II. Related Work

Data privacy and algorithmic bias are two of the ethical issues that Kedi et al., [17] has explored in addition to the technical difficulties of applying machine learning, which include algorithm complexity, system integration, and data quality. To also talk about the limits that are unique to SMEs, such as limited resources and a lack of technical knowledge. The future is bright for new technologies like reinforcement learning and deep learning, and there will be helpful suggestions for SMEs on how to make the most of these developments. In order to achieve long-term success and a leg up in the digital economy, the conclusion stresses the need of using machine learning.

For the Chinese market, Liu et al. [18] constructed 34 stock price determinants and then used Bayesian optimization to train four models: RF, DNN, GBDT, besides Adaboost. These models are then used to predict the closing prices of innovative SMEs that too relisted the following day. This study covers the period from July 22, 2019, to September 10, 2021 and uses 78,708 samples from 337 SMEs listed on the STAR market. Based on the experimental results, the Random Forest (RF) and Deep Neural Network (DNN) models [16] outperformed the Gradient Boosting Decision Tree (GBDT) and Adaptive Boosting (AdaBoost) models in terms of the evaluation metrics: Coefficient of Determination ($R^2$), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), thereby demonstrating superior prediction performance.

In order to enhance manufacturing processes, particularly for SMEs, Cruz et al. [19] propose a methodology for incorporating a completely automated procedure that uses automated machine learning algorithm. The approach is based on using the created models as objective functions of a non-dominated sorting genetic procedure that uses reference points. This sorting algorithm then produces production processes that are pareto-optimal based on preferences. A small manufacturing enterprise's production process data was used to execute and evaluate the technique, which resulted in very accurate models for the indicators that to be analyzed. In comparison to the results achieved using the conventional trial-and-error approach that focused solely on productivity, step of the suggested methodology was able to raise manufacturing process productivity by 3.19% and decrease defect rate by 2.15%.

In order to boost teamwork among SMEs promote innovation, and drive economic development, Wang, & Zhang [20] suggested using the XGBoost procedure in conjunction with IoT data. Internet of Things (IoT) and machine learning's part in fostering long-term economic growth in specific areas. In today's cutthroat business environment, staying ahead of the curve requires constant technological innovation. This article takes a look at how geography and environmental factors have affected economic development in different parts of China. Through performance evaluation, it contributes to regional economic success by focusing on SME coupling and coordination. Integrating IoT devices gives SMEs access the real-time data, which allows them to get profound insights into production, supply networks, and consumer behavior. At the same time, the XGBoost algorithm evaluates the data effectively and finds useful insights. The data from 11 provinces along the Yangtze River economic belt shows that between 2015 and 2020, Jiangsu Province will have the best regional innovation performance. The practical outcomes, supported by datasets that combine data from these provinces, demonstrate the promise of this strategy driven by the Internet of Things and XGBoost. With an astounding accuracy rate of 91.7%, this research highlights how effective this integrated strategy is in optimizing SME processes, outperforming rival machine learning techniques RF, and LR. It also calculates the ranking of the innovation environment, the mean value. Across 30 provinces in China, the average innovation degree was 0.1624.

SMEs are an important part of most economies' job markets, and Litvinenco has [21] focused on assessing their credit risk. The regulator claims that there is a lack of practical application of ML approaches, even though these methods can improve capital requirements assessments and open up financial services to this segment. One possible explanation is that financial firms are compelled to utilize simpler models due to the total complexity of explainability and interpretability. The benefits of these techniques are not always obvious, which is another factor. This research suggests a decision tree/logistic regression hybrid model to solve the complexity issue. With interpretability complexity on par with logistic regression, this model outperforms Random Forest and XGBoost. Their purpose is to differentiate a model's misclassifications based on their capital significance and to give an idea of the total capital supplies that a model is capable of producing. By comparing the models using these and other generally used measures, the financial institutions are able to make a better-informed judgment on which model would best satisfy their objectives?

Using authorized invoice data from 425 SMEs in Chongqing, Huang et al., [22] has concentrated on company performance statistics. In order to understand the feature contribution of a particular output, a prediction classifier was built using logistic regression, random forest, support vector machine, and soft voting ensemble learning methods. This classifier was then merged with the SHAP value. Consequently, our study demonstrated a robust association between the extracted characteristics and future defaults, paving the way for the prediction of companies' financial success.

To address the issue of SMEs' unbalanced in SCF using deep learning (DRL), Zhang et al., [23] proposed a new method they term DRL-Risk. To propose an instance-based account, taking into account the actual damage caused SMEs, and formulates the ICRP process. To then suggest a decision-policy deep duelling neural network for predicting SMEs' credit risk. The DRL-Risk method can use deep reinforcement learning to focus on SMEs that are most likely to incur large losses financially. The experimental results show that when compared to the baseline approaches in recall, G-mean, and financial loss, the DRL-Risk methodology may greatly improve the performance of predicting the credit risk of SMEs in SCF.

## III. Proposed Methodology

### A. Data Collection

Although the organization has a production management information system, it does not have much of a presence on the Internet. In the absence of a comprehensive digital strategy, the company is contemplating the implementation of autonomous production processes, sensor networks for the Internet of Things, and predictive maintenance systems. It can take part in the flow of information between suppliers and customers to some extent.

The use of straightforward economic software facilitates interaction with other branches of governmental administration. Data becomes more important to a software-controlled, dynamic Internet presence. Supply besides demand chain info flows, such as collaborative virtual archives, real-time big data, are being considered as part of an overall digital strategy.

To fully understand how SMEs engage with cyber-physical smart factories, cognitive automation, and Industry 4.0 wireless networks, it is necessary to first address SMEs after a quick overview of the concept. According to the European Commission, the number of employees and revenue are the main requirements for qualifying SMEs.

These requirements are provided in Table I. Certain businesses are the only ones that must meet these standards [24]. Companies are considered small if they have less than 50 workers and yearly sales of up to €10 million, and medium-sized if they have less than 250 employees and yearly to €50m million, meaning they have a balance sheet of up to €43 million.

Table I shows that there are several ways in which businesses can be assessed for their preparedness for this undertaking. These range from strategy and organization to smart factories, manufactured commodities, decision-making processes driven by big data, and human resources [25]. In the methodical approach of secondary analysis, the research questions are formed initially, and then the dataset is located and evaluated in great detail. Consequently, the primary objective of determine which obstacles hinder European SMEs the most when it comes to implementing Industry 4.0. Researchers drew on a variety of secondary data sources—including peer-review the academic articles, books, government records, and company annual reports—to compile the information needed to complete the study.

TABLE I Categorization of SMEs

| Company Category | Turnover | Staff Headcount | Balance Sheet Total |
|---|---|---|---|
| Medium-sized | ≤€50 m | <250 | ≤€43 m |
| Small | ≤€10 m | <50 | ≤€10 m |
| Micro | ≤€2 m | <10 | ≤€2 m |

A variety of screening and quality evaluation methods were used in the analysis, including data from the European Commission, the Organisation for Economic Co-operation and Development (OECD), and tools such as Distiller Systematic Review (DistillerSR), Mixed Methods Appraisal Tool (MMAT), Risk of Bias in Systematic Reviews (ROBIS), and the Systematic Review Data Repository (SRDR).The SME Alliance's secondary data analysis was also used to perform the research. The following scientific procedures to be employed to data: i) the analytical technique that breaks down a large research problem into smaller ones in order to better understand it. In this study, the used: (i) analysis, which involved searching domestic and foreign literature in the designated research area for relevant information; (ii) synthesis, which involved processing and combining previously acquired knowledge; and (iii) comparison, which involved finding a knowledge, phenomena, or objects in order to learn more about the studied issue. (iv) the investigating strategy that was employed to discover more about the current issue. This method was utilized in this study to interpret the results of the analyses. Its purpose is to draw theoretical conclusions about the research problem based on the examined knowledge, which is prearranged dependencies. Comparative analysis was also a part of the investigation. Of the 268 companies surveyed in Germany, 56.5% did not fully comply with the requirements for implementing Industry 4.0 [26]. For the novice level 1 implementation approach, 20% of respondents are just somewhat prepared. Table II shows that just 0.3% met all five requirements at the exceptional level of execution.

To find out how ready companies are for Industry 4.0, a poll was run. Fifteen hundred chief executive officers (CXOs) from nineteen different nations took part. While 20% of chief executive officers said their companies are ready for a new business model, only 14% said to "extremely confident" in their ability to answer the problems of Industry 4.00. Despite the need for significant changes, 84% of educate their personnel and only 25% thought their employees to completely incorporate Industry 4.0. Less than one-fifth of people who took the survey felt adequately ready for intelligent and autonomous technologies. On a 15-year time frame, Fig. 1 shows the amount of SMEs in the EU [27]. The proliferation of these firms is plain to see.

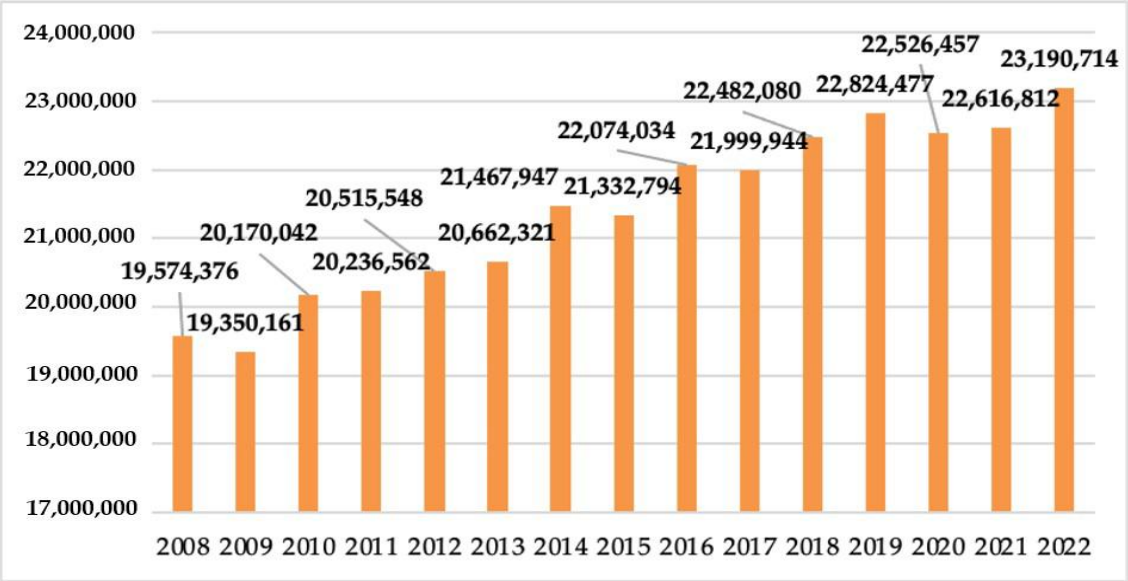


Fig. 1. Sum of SMEs in the European Union (EU27) from 2008 to 2022. Basis: Authors' gathering [27].

Nearly 23 million people called them home in 2022. The first step for SMEs is to automate their administrative and marketing processes. The hardest part of starting a business is often the first step. Strong technological complementarities might encourage future adoption after an initial shift to digital know-how. Many small and medium-sized enterprises (SMEs) depend on external systems, assistance, and guidance to accomplish these and other digital technology goals. There are financial considerations as they need to make up for a lack of internal capacity, thus this is done. Take digital platforms like e-commerce marketplaces and social networks as an example. They provide a great chance to improve some activities while keeping costs down, including data analytics and business intelligence services. To a similar extent, SMEs manage digital security risks by using external consultants or incorporating security-by-design into their digital services. Knowledge marketplaces provide AI solutions, and cloud-based software as a service allows them to skip the introduction of new AI systems. Autonomous mobile robots use cloud computing, image recognition, smart manufacturing, and real-time monitoring. The use of data analytics, imaging and sensing tools, and virtual reality simulations are all components of digital twin-driven smart manufacturing. In smart industrial settings, collaborative autonomous systems use cloud computing analytics, mobile robotic equipment, and tools for acquiring and analyzing images.

When it comes to digital disparities, technical complementarities might make things worse as bigger and better-informed companies can afford to use more sophisticated digital strategies. Enterprise CRM production process integration, and data analytics are all examples of more advanced technologies that highlight the gap between SMEs and larger companies.

It is necessary to high the benefits and drawbacks of Industry 4.0 technologies before assessing implementation hurdles. The irregularities in the deployment of Industry 4.0 must be described and characterized correctly. While there are certainly obstacles to overcome before big data-driven technologies can be completely utilized, industrial artificial intelligence can enhance production capabilities and productivity, leading to higher profitability. Rapid and configurable operations, including storage cost savings, allow for 10-30% cheaper costs in mass manufacturing, which is the greatest advantage of implementing Industry 4.0. Another perk is the possibility of a ten to thirty percent drop in logistics and quality control costs.

Worker output, environmental impact, and overall efficiency can all benefit from more effective use of energy and natural resources, which can boost productivity by 15–20%. Consequently, the manufactured goods may be made and delivered to clients faster. Industry 4.0 encourages steady economic expansion by highlighting state-of-the-art industrial manufacturing methods. There are ever-changing tests that SMEs face while trying to embrace Industry 4.0. Given the interconnected nature of the factors that slow down or speed up the adoption of new technology, this study will also evaluate the potential benefits of using the suggested deep learning model to help SMEs overcome implementation hurdles.

TABLE II STAGES OF IMPLEMENTATION

| Level | Designation |
|---|---|
| 0 | Expert |
| 1 | Top Performer |
| 2 | Intermediate |
| 3 | Experienced |
| 4 | Top Performer |
| 5 | Intermediate |

### B. Contrastive Learning of Visual Representations

In order to forecast the output of data, the study makes use of deep learning. $E(\bullet)$ is the symbol for the encoder, which is able to transform the data into two representations, r′ and r″, by removing any semantic information. The Vision Transformer

(ViT) [28] is a source of inspiration for our light encoder construction LTrans in our framework. It gets pictures r′ and r″ as Eq. (1) shows, where the yield r′ ∈ $R^d$ is created layer.

$$r' = e(i') \tag{1}$$

To change the input of the standard Transformer—a 1D embeddings—into a series of 2D flattened patches with dimensions N × P2 • C, instead of the data being reshaped from H × W × C. The original data's height and width are indicated by the H and W in this case. The size of the C stands for the number of channels. Each data patch's resolution, denoted as P2, and the total number of patches are determined by Eq. (2).

$$N_{patch} = (HW \vee P)^2 \tag{2}$$

To first flatten the patches using the original data shaper, then project them into D dimensions using a linear projection with trainable parameters. In Eq. (3), we can see the linear projection, with ip standing for the 2D patches that are flattened from the initial data set i. An i_class is a unique token for a categorization. This is very much like the BERT [CLS] token [29]. Patch embeddings are the results of this projection. The position embeddings are put to use, $e_{position}$ to maintain the data regarding the positions. To generate position embeddings using typical learnable 1D methods, then combine them embeddings to form the final embedded patches E_0. Afterwards, the LTrans is fed embedded patch data.

$$E_0 = e_{position} + \left[i_{class}; i_p^1 e; i_p^2 e; \ldots; i_p^N e\right], e \in R^{(P^2.C)\times D}, e_{position} \in R^{(N+1)\times D} \tag{3}$$

To add a normalization every component and a residual both component to LTrans, which comprises of MLP blocks. A large number of academics are interested in incorporating multi-head attention into their models. To be more specific, let's pretend to have an input sequence$x \in R^{N\times D}$. To calculate sum over each charge V in the input arrangement x, as Eq. (4) shows. The sights of attention $Attention_{mn}$ are found by comparing the query representations of two elements in the arrangement and their pairwise similarity. $Q^m$ and key $K^n$, as Eq. (5) shows. Lastly, $Sa$ is calculated by the Eq. (6).

$$[Q, K, V] = xU_{QKV}, U_{QKV} \in R^{D\times 3D_h} \tag{4}$$

$$Attention = softmax\frac{QK^T}{\sqrt{D_h}}, Attention \in R^{N\times N} \tag{5}$$

$$Sa(x) = AttentionV \tag{6}$$

The outputs of k self-attention procedures are projected together by multi-head self-attention (MSA), as demonstrated in Eq. (7).

$$MSA(x) = [Sa_1(x); Sa_2(x); , \ldots Sa_k(x)]U_{QKV}, U_{QKV} \in R^{k.D_h\times D} \tag{7}$$

Two completely linked layers with GELU non-linearity make up the MLP chunks in the LTrans. In Eq. (8) and Eq. (9), the full Ltrans procedure is detailed.

$$x_l' = MSA\big(Norm(x_{l-1})\big) + x_{l-1}, l = 1 \ldots L \tag{8}$$

$$x_l = MLP\big(Norm(x_l')\big) + x_l', l = 1, \ldots, L \tag{9}$$

Projection head $p(\cdot)$may transpose the illustration r to a different feature interplanetary z using a tiny non-linear multi-layer perceptron neural network. The ғ is a non-linear ReLU function, as seen in Eq. (10). The $W^{(1)}$ is encoder $e(\cdot)$, and the $W^{(2)}$ is weight projection head $p(\cdot)$.

$$z = p(r) = W^{(2)}\sigma\big(W^{(1)}r\big) \tag{10}$$

Our final model is the result of combining the four parts listed above. This algorithm determines to have size N, constant τ, encoder e, projection head p, and data expansion module A. pass the data into the encoder $e(\cdot)$ and projection head $p(\cdot)$. After that, to do the pairwise similarity and calculate the encoder $e(\cdot)$ besides forecast head $p(\cdot)$. Finally, to produce a network$e(\cdot)$, then head. To will use this encoder $e(\cdot)$in order to create the unlabeled dataset's foundational data representations, and then feed that knowledge into our model so it can perform the classification task.

- Underlying Knowledge Based Multi-Layer Perceptron Classifier (UKMLP)

With the help of the restricted labelled data, the UKMLP attempts to refine the feature representation learnt by the aforementioned model. Here, to take a page out of transfer learning's playbook by enhancing the traditional classifier's architecture. Specifically, to add 12 hidden layers, with the following configuration: three layers of 256 layers of 512 neurons connected, two layers of 1024 connected, and three layers of 256 neurons connected. The three components of the design are the input layer, two hidden layers, and the output layer. After receiving input from model up top, the underlying knowledge is passed on to the buried layers. The output layer's neuron counts changes depending on the dataset's classes. As shown in Eq. (11) it adheres to a rectified linear activation for every hidden layer. If x is less than zero, the ReLU function returns zero as an output; otherwise, it returns the input value.

$$f(x) = max(0, x) \tag{11}$$

The UKMLP loss function, multi-class entropy, is illustrated in equation (12). Here, yˆ vector y containing the actual class label, is a one-hot representing the predicted class probabilities for all C classes, and the natural logarithm is represented by the log.

$$L(y\hat{}, y) = -\sum_{i=1}^{C} \quad y_i log(y\hat{}_i) \tag{12}$$

- Fine-tuning using Artificial protozoa optimizer

Here to present the APO algorithm, which is used to fine-tune the UKMLP model's parameters using its mathematical models that mimic protozoa.

*1) Mathematical models*: This section presents the algorithm that can be used to solve the minimization problem. For metaheuristic algorithms, the solution set representation is crucial. Each protozoan in our suggested method occupies a certain location inside the solution set, which is represented by $dim$ variables.

*2) Foraging*: When studying protozoa foraging behavior, to took both internal and extrinsic influences into account. The protozoa's feeding habits are an example of an internal factor,

whereas species collisions and competing behaviors are examples of external variables.

*3) Autotrophic mode*: In order to sustain themselves, protozoans can use chloroplasts to make carbs. The protozoan will relocate to a spot with lo To r light intensity if it is exposed to very bright light. When it's in a dimly lit area, the inverse is true. Taking into consideration the light levels surrounding the *j*th protozoan is suitable will move to the site of the *j*th protozoan. Our mathematical model for mode is as follows:

$$X_i^{new} = X_i + f. \quad (13)$$

$$X_i = \left[x_i^1, x_i^2, \dots, x_i^{dim}\right] X_i = sort(X_i) \quad (14)$$

$$f = rand.\left(1 + cos\left(\frac{iter}{iter_{max}}.\pi\right)\right) \quad (15)$$

$$np_{max} = \left[\frac{ps-1}{2}\right] \quad (16)$$

$$w_a = e^{-} \quad (17)$$

$$M_f[d_i] = \{1, if\, d_i is \in randperm\left(dim, \left[dim.\frac{i}{ps}\right]\right)\ 0, otherwise \quad (18)$$

where $X_i^{new}$ and $X_i$ denote the efficient position, besides original site of the $i$th protozoan, respectively. $X_j$ is the randomly designated *j*th protozoan. $X_{k-}$ Represents a randomly selected protozoan in the $k$th paired than $i$. Precisely, if $X_i$ is $X_1$, $X_{k-}$ is also set as $X_1$. $X_{k+}$ denotes a haphazardly s $k$th paired neighbor, besides its rank directory is greater than $i$. Particularly, if $X_i$ is $X_{ps}$, $X_{k+}$ is also set to $X_{ps}$, where $ps$ is the population size. $f$ represents a foraging factor and $rand$ denotes a random number in the distribution. $iter$ besides $iter_{max}$respectively. $np$ indicates the number of neighbor pairs among the external factors and $npmax$ is the maximum charge of $np$. $w_a$ is mode and $eps(2.2204e-16)$ is a significantly small sum. $\odot$ denotes the Hadamard product. $M_f$ is a size of $(1 \times dim)$, where every element is 0 or 1. $d_i$ index $d_i \in \{1,2, \dots, dim\}$.

- Heterotrophic style

A protozoan can get its nourishment by soaking up organic stuff when it's dark. With the expectation that $X_{near}$ is close by and has plenty of food, the protozoan will go there. This mathematical model is proposed for the heterotrophic mode.

$$X_i^{new} = X_i + f\left(X_{near} - X_i + \frac{1}{np}.\sum_{k=1}^{np} w_h.(X_{i-k} - X_{i+k})\right)\odot M_f \quad (19)$$

$$X_{near} = \left(1 \pm Rand.\left(1 - \frac{iter}{iter_{max}}\right)\right)\odot X_i \quad (20)$$

$$w_h = e^{-\left|\frac{f(X_{i-k})}{f(X_{i+k})+eps}\right|} \quad (21)$$

In order to sustain themselves, protozoans can use chloroplasts to make carbs. The protozoan will relocate to a spot with light intensity if it is exposed to very bright light. When it's in a dimly lit area, the inverse is true. Taking into consideration the light levels surrounding the *j*th protozoan is suitable will move to the site of the *j*th protozoan. Our mathematical model for mode is as follows:

$$X_i^{new} = X_i + f. \quad (13)$$

$$X_i = \left[x_i^1, x_i^2, \dots, x_i^{dim}\right] X_i = sort(X_i) \quad (14)$$

$$f = rand.\left(1 + cos\left(\frac{iter}{iter_{max}}.\pi\right)\right) \quad (15)$$

$$np_{max} = \left[\frac{ps-1}{2}\right] \quad (16)$$

$$w_a = e^{-} \quad (17)$$

$$M_f[d_i] = \{1, if\, d_i is \in randperm\left(dim, \left[dim.\frac{i}{ps}\right]\right)\ 0, otherwise \quad (18)$$

where $X_i^{new}$ and $X_i$ denote the efficient position, besides original site of the $i$th protozoan, respectively. $X_j$ is the randomly designated *j*th protozoan. $X_{k-}$ Represents a randomly selected protozoan in the $k$th paired than $i$. Precisely, if $X_i$ is $X_1$, $X_{k-}$ is also set as $X_1$. $X_{k+}$ denotes a haphazardly s $k$th paired neighbor, besides its rank directory is greater than $i$. Particularly, if $X_i$ is $X_{ps}$, $X_{k+}$ is also set to $X_{ps}$, where $ps$ is the population size. $f$ represents a foraging factor and $rand$ denotes a random number in the distribution. $iter$ besides $iter_{max}$respectively. $np$ indicates the number of neighbor pairs among the external factors and $npmax$ is the maximum charge of $np$. $w_a$ is mode and $eps(2.2204e-16)$ is a significantly small sum. $\odot$ denotes the Hadamard product. $M_f$ is a size of $(1 \times dim)$, where every element is 0 or 1. $d_i$ index $d_i \in \{1,2, \dots, dim\}$.

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$$X_{near} = \left(1 \pm Rand.\left(1 - \frac{iter}{iter_{max}}\right)\right)\odot X_i \quad (20)$$

$$w_h = e^{-\left|\frac{f(X_{i-k})}{f(X_{i+k})+eps}\right|} \quad (21)$$

$$Rand = [rand_1, rand_2, \dots, rand_{dim}] \quad (22)$$

where $X_{near}$ is a nearby site, and ''±'' implies that $Xnear$ can be in dissimilar instructions from the $i$th protozoan. $X_{i-k}$ denotes the $(i-k)$th protozoan the $k$th paired index is $i-k$. Specifically, if $X_i$ is $X_1$, $X_{i-k}$ is also set to $X_1$. $X_{i+k}$ represents the $(i+k)$th protozoan designated from the $k$th paired index is $i+k$. Particularly, if $X_i$ is $X_{ps}$, $X_{i+k}$ is also set to $X_{ps}$. $w_h$ is factor in the heterotrophic mode. $Rand$ is elements in the [0,1] intermission as given in Eq. (22).

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*4) Dormancy*: As a defense mechanism against harsh environments, protozoans can go into a dormant state when threatened. In order to keep the number of protozoa constant, they replace dormant protozoans with newly created ones. The following is the mathematical model of dormancy:

$$X_i^{new} = X_{min} + Rand \odot (X_{max} - X_{min}) \quad (23)$$

$$X_{min} = [lb_1, lb_2, \dots, lb_{dim}]\ X_{max} = [ub_1, ub_2, \dots, ub_{dim}] \quad (24)$$

where $X_{min}$ and $X_{max}$ represent the vectors, respectively. $lb_{di}$ and $ub_{di}$ indicate the of the $di$th variable, correspondingly.

*5) Reproduction*: When protozoa are mature and in good health, they reproduce asexually by a process called binary fission. This kind of reproduction should theoretically result in the protozoan dividing into two females that are genetically identical. To able this behavior by creating an identical protozoan and then taking perturbation into account. How about this for a mathematical model of reproduction:

$$X_i^{new} = X_i \pm rand.\left(X_{min} + Rand \odot (X_{max} - X_{min})\right) \odot M_r \quad (25)$$

$$M_r[d_i] = \{1, if\, d_i is \in randperm(dim, [dim.rand])\ 0, otherwise \quad (26)$$

where ''±'' implies alarm forward besides reverse. $Mr$ is vector in replica procedure, whose size is $(1 \times dim)$, besides each element is 0 or 1.

*6) Algorithm*: Here are the specifics of the APO. Here are the parameters that are involved in integrating all the mathematical models:

$$pf = pf_{max}.rand \quad (27)$$

$$p_{ah} = \frac{1}{2}.\left(1 + cos\left(\frac{iter}{iter_{max}}.\pi\right)\right) \quad (28)$$

$$p_{ar} = \frac{1}{2}.\left(1 + cos\left(1 - \frac{i}{ps}.\pi\right)\right) \quad (29)$$

where $pf$ is a quantity fraction of latency besides reproduction in protozoa populace and $pf_{max}$ is the maximum charge of $pf$. $p_{ah}$ designates the likelihoods of heterotrophic behaviors, and $p_{dr}$ designates the likelihoods of dormancy besides imitation.

Note that the projected APO has limits: $np$ (sum of neighbor pairs) and $pf_{max}$ (maximum proportion fraction).

## IV. Results and Discussion

An NVIDIA TESLA P100 GPU with 16 GB of RAM and a XEON CPU of 13 GB RAM are used to execute the experiments in the study. The model's hyper-parameters are defined as follows: epochs=200, batch size=500, learning rate=0.01, projection dimension=64. Keras is used to implement the code with scikit-learn. Compare the proposed model to current methods using a variety of metrics in Table III, which displays the results of the validation analysis.

TABLE III Comparative Analysis of Proposed Model with Existing Models

| Model | MAPE | MSE | RMSE | R2 |
|---|---|---|---|---|
| DBN | 41.6 | 0.021 | 0.144 | 0.776 |
| CNN | 39.29 | 0.020 | 0.132 | 0.805 |
| LSTM | 52.99 | 0.019 | 0.245 | 0.735 |
| Proposed model | 29.95 | 0.013 | 0.116 | 0.905 |

Table III and Fig. 2 presents a comparative investigation of the planned model against existing models (DBN, CNN, and LSTM) using presentation metrics such as MAPE, MSE, RMSE, besides $R^2$. The proposed model shows the best performance with the lowest MAPE of 29.95, significantly outperforming DBN (41.6), CNN (39.29), and LSTM (52.99). For MSE, the proposed model also achieves the lowest value at 0.013, compared to DBN (0.021), CNN (0.020), and LSTM (0.019). In terms of RMSE, the projected model exhibits the smallest error at 0.116, while DBN, CNN, and LSTM have values of 0.144, 0.132, besides 0.245, correspondingly. Finally, the $R^2$ charge of the projected model is the uppermost at 0.905, indicating superior predictive accuracy compared to DBN (0.776), CNN (0.805), and LSTM (0.735). Overall, the proposed model significantly outperforms existing models across all metrics.

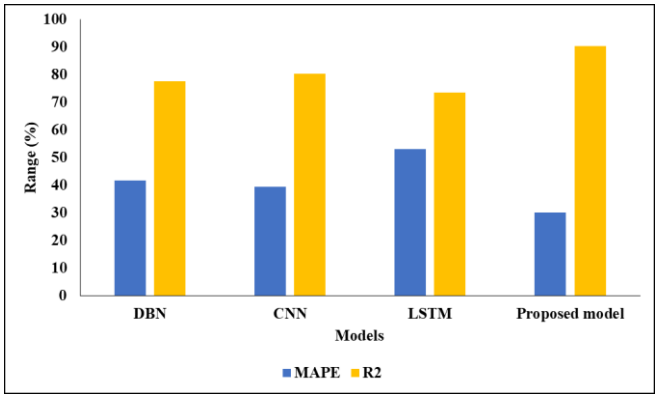


Fig. 2. Visual representation of proposed model.

TABLE IV ERROR ANALYSIS OF DIFFERENT MODELS

| Metric | Algorithm | | | | |
|---|---|---|---|---|---|
| | Proposed | LSTM | RNN | CNN | DBN |
| R2 | 0.98 | 0.96 | 0.956 | 0.94 | 0.93 |
| Mean Squared Error (MSE) | 0.0065 | 0.042 | 0.037 | 0.036 | 0.0325 |
| Root Mean Squared Error (RMSE) | 0.0803 | 0.095 | 0.091 | 0.099 | 0.108 |
| Mean Absolute Percentage Error (MAPE) | 0.0702 | 0.0966 | 0.086 | 0.089 | 0.0938 |
| Mean Absolute Error (MAE) | 0.0567 | 0.0634 | 0.0648 | 0.0743 | 0.1305 |

*1)* Comparative Analysis of Proposed model on error analysis

The error analysis of various algorithms is tested and results are averaged in Table IV.

In the analysis of R2, the existing ML and DL models are tested and achieved nearly 93% to 95%, where LSTM achieved 96% and proposed model achieved 98%. This is because the research work uses the optimizer for fine-tuning the parameters of the proposed model and existing models uses the manual learning rate and leads to high computational complexity. The existing DBN achieved 0.03 of MSE and 0.108 of RMSE, where RNN achieved 0.037 of MSE and 0.091 of RMSE and leads to high computational complexity issues than proposed model. The MAE of proposed model has only 0.0567 and the existing ML and DL achieved nearly 0.064 to 0.074 of MAE leads to increase the chance of error rate in detecting process. From the analysis, it is clearly shown that the proposed model achieved better performance than existing models such as DBN, CNN, RNN and LSTM models.

*2)* Experimental analysis of the proposed model on different iterations

Table V and VI presents the experimental analysis of proposed model on different iterations by considering with and without APO optimizer.

The performance of the proposed model was evaluated in terms of error metrics, including R-squared (R2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE), across multiple iterations. The results were analyzed both without optimization and with the APO optimizer. Table V presents the error analysis of the proposed model across 10 iterations without optimization. The average R2 value achieved is 0.9950, indicating strong predictive performance. However, the other error metrics show fluctuations across different iterations. Notably, iteration 2 exhibits a lower R2 value (0.9893) and higher error values (MSE = 0.0312, RMSE = 0.1766, MAPE = 0.0255, and MAE = 0.1263), suggesting reduced accuracy in that particular run. Conversely, iteration 10 records a higher R2 value (0.9979) and lower MSE (0.0056), RMSE (0.0748), MAPE (0.0097), and MAE (0.0559), indicating more stable performance. The inconsistency in error values suggests that without optimization, the model exhibits variability in prediction accuracy across iterations.

TABLE V ERROR ANALYSIS OF PROPOSED MODEL ON DIFFERENT ITERATIONS

| **Number of iterations** | Proposed with various iteration without optimization | | | | |
|---|---|---|---|---|---|
| | **R2** | **MSE** | **RMSE** | **MAPE** | **MAE** |
| 1 | 0.9981 | 0.0052 | 0.0721 | 0.0099 | 0.0529 |
| 2 | 0.9893 | 0.0312 | 0.1766 | 0.0255 | 0.1263 |
| 3 | 0.9975 | 0.0066 | 0.0815 | 0.0095 | 0.0501 |
| 4 | 0.9927 | 0.0212 | 0.1456 | 0.0216 | 0.1101 |
| 5 | 0.9928 | 0.0211 | 0.1454 | 0.0210 | 0.1090 |
| 6 | 0.9977 | 0.0060 | 0.0777 | 0.0100 | 0.0560 |
| 7 | 0.9934 | 0.0194 | 0.1391 | 0.0207 | 0.1055 |
| 8 | 0.9978 | 0.0060 | 0.0772 | 0.0096 | 0.0529 |
| 9 | 0.9926 | 0.0216 | 0.1471 | 0.0219 | 0.1110 |
| 10 | 0.9979 | 0.0056 | 0.0748 | 0.0097 | 0.0559 |
| Average | 0.9950 | 0.0144 | 0.1137 | 0.0159 | 0.0830 |

TABLE VI ANALYSIS OF PROPOSED MODEL IN TERMS OF ERROR RATE WITH APO OPTIMIZER

| Number of iterations | various iteration with optimization | | | | |
|---|---|---|---|---|---|
| | R2 | MSE | RMSE | MAPE | MAE |
| 1 | 0.9981 | 0.0048 | 0.0690 | 0.0078 | 0.0460 |
| 2 | 0.9970 | 0.0054 | 0.0738 | 0.0097 | 0.0608 |
| 3 | 0.9973 | 0.0072 | 0.0849 | 0.0115 | 0.0616 |
| 4 | 0.9986 | 0.0032 | 0.0567 | 0.0100 | 0.0517 |
| 5 | 0.9975 | 0.0069 | 0.0828 | 0.0135 | 0.0697 |
| 6 | 0.9992 | 0.0029 | 0.0541 | 0.0088 | 0.0510 |
| 7 | 0.9992 | 0.0016 | 0.0399 | 0.0053 | 0.0338 |
| 8 | 0.9975 | 0.0071 | 0.0843 | 0.0133 | 0.0689 |
| 9 | 0.9983 | 0.0041 | 0.0638 | 0.0123 | 0.0596 |
| 10 | 0.9960 | 0.0114 | 0.1069 | 0.0164 | 0.0858 |
| Average | 0.9978 | 0.0055 | 0.0716 | 0.0109 | 0.0589 |

Table VI presents the performance of the model when optimized using the APO optimizer. The results indicate a notable improvement in performance. The average R2 value increases to 0.9978, demonstrating enhanced model reliability. Additionally, the error values significantly decrease, with MSE dropping to 0.0055, RMSE to 0.0716, MAPE to 0.0109, and MAE to 0.0589. The lowest MSE value (0.0016) and RMSE value (0.0399) occur in iteration 7, corresponding to an exceptionally high R2 value of 0.9992, signifying excellent model accuracy. The highest error values are observed in iteration 10 (MSE = 0.0114, RMSE = 0.1069, MAPE = 0.0164, MAE = 0.0858), yet these values remain significantly lower compared to the non-optimized model.

A comparison between the two approaches clearly demonstrates the advantage of using the APO optimizer. The reduction in error values across all metrics indicates that the optimization process successfully enhances model accuracy and stability. Notably, APO optimization effectively minimizes variations in model performance, ensuring consistency across iterations. The improvement in R2 values confirms that the optimized model maintains a stronger correlation between predictions and actual values, leading to more reliable outcomes.

## V. CONCLUSION

This study identified lack of capital and skilled workforce as the primary barriers preventing European SMEs from adopting Industry 4.0 technologies. Successful implementation depends not only on financial resources but also on strong leadership, strategic planning, and continuous skill development. The proposed model can guide SMEs in prioritizing digitalization steps and securing support through training and funding schemes. Importantly, Industry 4.0 is not exclusive to large firms—SMEs, with proper planning and resources, can also participate effectively. Future work will focus on developing cost-efficient AI-based training platforms to upskill SME workforces in Industry 4.0 technologies. Integration of real-time data from SME pilot implementations can further validate the UKSSL framework. Research can also explore decentralized financing models to ease capital constraints. Additionally, collaborative innovation hubs may support knowledge sharing and reduce adoption barriers.

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# An Improved Sparrow Search Algorithm for Flexible Job-Shop Scheduling Problem with Setup and Transportation Time

Yi Li[1], Song Han[2], Zhaohui Li[3], Fan Yang[4], Zhengyi Sun[5]
School of Maritime Economics and Management, Dalian Maritime University, Dalian China[1, 2, 3]
Hangzhou Hollysys Automation Co., Ltd. Xi 'an branch, Xi'an China[4]
Graduate School of Information, Production and Systems, Waseda University, Kitakyushu Japan[5]

***Abstract*—This study addresses the low production efficiency in manufacturing enterprises caused by the diversification of order products, small batches, and frequent production changeovers. Focusing on minimizing the makespan, this study establishes a Flexible Job-Shop Scheduling Problem (FJSP) model incorporating machine setup and workpiece transportation times, and proposes an improved sparrow search algorithm to effectively solve the problem. Based on the sparrow search algorithm, this study proposes a novel location update strategy that expands the search direction in each dimension and strengthens each individual's local search capability. In addition, a critical-path-based neighborhood search strategy is introduced to enhance individual search efficiency, and an earliest completion time priority rule is employed during population initialization to further improve solution quality. Several experiments are conducted to validate the effectiveness of the improved strategy, and the results are compared with those obtained using the particle swarm optimization and gray wolf optimization algorithms to demonstrate the efficiency of the proposed model and algorithm. The improved sparrow search algorithm can effectively generate feasible solutions for large-scale problems, provide practical manufacturing scheduling schemes, and enhance the production efficiency of manufacturing enterprises.**

***Keywords*—Flexible job shop scheduling; machine setup; transportation; sparrow search algorithm; earliest completion time priority***

## I. INTRODUCTION

The Flexible Job Shop Scheduling Problem (FJSP) is a key area in modern manufacturing. The growing complexity of market demands, such as product diversification, small-batch production, and frequent changeovers, has intensified the need to consider setup and transportation times in production scheduling. This makes FJSP research incorporating these factors, a critical academic focus.

Scholars have conducted extensive research on the flexible job shop scheduling problem under single constraints, either setup time or transportation time. Defersha et al.[1], investigated the flexible job shop scheduling problem considering worker-machine setup times and proposed an improved simulated annealing algorithm to solve it. Li et al.[2], proposed an improved artificial immune system algorithm to solve the flexible job shop scheduling problem considering setup scenarios. Peng et al.[3], investigated the multi-objective flexible job shop scheduling problem with job transportation time and learning effect constraints, and proposed a hybrid discrete multi-objective imperialist competitive algorithm to solve the model. Zhang Guohui et al. [4], examined the impact of machine installation, positioning, and other adjustment times on the flexible job shop scheduling problem, and proposed an improved genetic algorithm to solve the problem. Sadrzadeh [5], proposed a hybrid artificial immune-particle swarm optimization algorithm and validated its effectiveness through numerical experiments. Zhang et al.[6], designed a genetic algorithm with a tabu search procedure to solve the flexible job shop scheduling problem with transportation constraints and limited processing times. The aforementioned scholars have proposed various algorithms to address the FJSP with either setup or transportation times separately considered. However, these studies have overlooked the interactions among processing, setup, and transportation times. Setup times affect the start time of processing tasks, whereas processing times determine the start time of transportation tasks. The combined effects of setup and transportation times result in varying machine waiting times. Therefore, flexible job shop scheduling problem that simultaneously incorporates setup and transportation times is more consistent with real-world production scenarios.

For the flexible job shop scheduling problem that incorporates both setup and transportation times, An et al.[7], proposed a hybrid multi-objective evolutionary algorithm based on a Pareto elite storage strategy, aiming at minimizing the makespan, total delay, total production cost, and total energy consumption. Li et al.[8], simultaneously optimized energy consumption and makespan, employing an improved Jaya algorithm to solve the problem. Zhang et al.[9], proposed an effective heuristic algorithm to minimize the makespan and total energy consumption. Sun et al.[10], developed a hybrid multi-objective evolutionary algorithm aimed at minimizing makespan, total workload, critical machine workload, and penalties for early or late completion. Rossi [11], investigated the flexible job shop scheduling problem incorporating both transportation and setup times, employing an ant colony algorithm enhanced with pheromone mechanisms. In summary, the primary approaches for solving the flexible job shop scheduling problem encompass exact algorithms based on mathematical programming, as well as intelligent evolutionary methods such as the Genetic Algorithm (GA) [12], Tabu Search

(TS) [13], Ant Colony Optimization (ACO) [14], and Particle Swarm Optimization (PSO) [15]. Traditional algorithms such as genetic algorithms and tabu search often encounter limitations when addressing these problems, including high dimensionality, slow convergence, and challenging parameter tuning. In 2020, Xue et al., proposed the Sparrow Search Algorithm (SSA) [16], a novel population-based intelligent optimization method characterized by simple principles, few parameters, and ease of implementation, and has been widely applied in various fields [17]. Although the SSA algorithm has also been applied to solve the FJSP, its application to the FJSP with simultaneous consideration of setup and transportation times remains relatively rare.

Based on the aforementioned background, this study incorporates the real production scenario of Dalian BL Technology Co., Ltd. and formulates an integer programming model for the flexible job shop scheduling problem, which considers both setup and transportation times, aiming to minimize the makespan. The effectiveness of the proposed algorithm is verified using the CPLEX solver. As the data scale increases, it becomes difficult for exact algorithms to solve the problem in a short time. This study introduces enhanced strategies, culminating in the design of an Improved Sparrow Search Algorithm (ISSA) to solve the problem. Finally, the effectiveness of these enhanced strategies and the efficiency of the ISSA algorithm are validated using the small-scale Kacem and medium-to-large-scale Brandimarte benchmark instances.

The remainder of this paper is organized as follows: Section II formulates the problem and constructs the mathematical model. Section III presents the encoding scheme and proposes the improved sparrow search algorithm. Computational experiments are conducted in Section IV, followed by results and discussions in Section V. Finally, conclusions are provided in Section VI.

## II. Problem Description and Model Construction

### A. Problem Description

Dalian BL Technology Co., Ltd. is a multi-sector, order-driven manufacturing enterprise. The orders they receive typically consist of small batches and a wide variety of parts. When processing different types of parts, the machines require adjustments such as changing tool heads and adjusting machine parameters. Additionally, when metal parts proceed to the next processing step, they often need to be transferred to different machines, and manual transport equipment is employed to move the parts. Building on this manufacturing scenario, the workshop scheduling problem can be formulated as a flexible job shop scheduling problem (FJSP) that incorporates both setup and transportation times, described as follows: there is a set of $n$ jobs, denoted by $J = \{J_1, J_2, \ldots, J_n\}$, and a set of $m$ machines, denoted by $M = \{M_1, M_2, \ldots, M_m\}$. Each job $J_i$ consists of $j$ operations, with the $j$ -th operation of job $J_i$ represented by $O_{ij}$. Each operation can be processed on one or more machines; however, each machine can process only one operation at a time. Once an operation starts on a machine, it cannot be interrupted. Operations within the same job must adhere to a prescribed sequence, whereas there are no sequencing constraints among operations from different jobs. At any given time, each job can be processed on only one machine. Before any machine can process a job, it must be adjusted by workers according to that job's characteristics; moreover, the machine requires re-adjustment when switching between jobs. When transferring a job's operation to a different machine, transport equipment is required to move the job.

The problem follows the standard constraints of the flexible job shop scheduling problem while additionally accounting for the effects of machine setup and transportation on the scheduling process. Based on real-world conditions and the scope of this research, the following constraints and assumptions are proposed:

- If a job is processed consecutively on the same machine, no transportation is required.
- If two or more consecutive operations on a machine belong to the same job, no setup time is required for the subsequent operation.
- Loading and unloading times are included in the overall transportation time.
- Human resources and transport equipment are sufficiently available and can respond in real-time.

### B. Scenario Analysis

In the actual manufacturing scenario, processing can begin only after setup is completed, thereby influencing the processing start time. Similarly, transportation can commence only once an operation finishes, affecting the start time of transportation. Furthermore, subsequent processing can begin only after the setup has been completed and the job has been transferred to the next machine. The combined effects of setup and transportation times influence the machine's waiting time. Consequently, setup, transportation, and processing times are interrelated.

Taking the extended Kacem 4×5 dataset as an example, if scheduling is carried out without accounting for setup and transportation times, the resulting plan is shown in Fig. 1(a). If this scheduling plan is applied directly in the workshop, a significant delay in the overall makespan will result, as illustrated in Fig. 1(b). However, after incorporating the effects of setup and transportation times on the makespan, the proposed model optimizes the scheduling plan, and the final outcome, depicted in Fig. 1(c), achieves a shorter makespan compared to the previous plan.

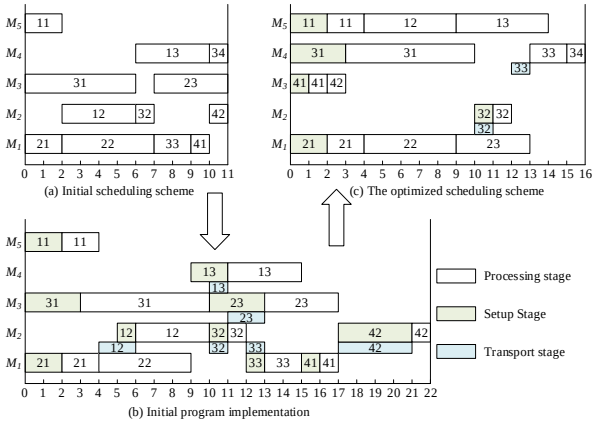



Fig. 1. Comparison of scheduling schemes

### C. Model Construction

The definitions of the model parameters are provided in Table I.

TABLE I. PARAMETERS OF FJSP MODEL WITH SETUP TIME AND TRANSPORTATION TIME

| Parameter | Definition |
|---|---|
| $J$ | Job set |
| $M$ | Machine set |
| $i, p$ | Job index |
| $J_i$ | A set of operations for job $i$ |
| $j, q$ | Operation index |
| $k, l$ | Machine index |
| $C_i$ | Completion time of job $i$ |
| $O_{ij}$ | Operation $j$ of job $i$ |
| $v_{ij}$ | Start transportation time of $O_{ij}$ |
| $u_{ij}$ | End transportation time of $O_{ij}$ |
| $s_{ij}$ | Start setup time of $O_{ij}$ |
| $Cmax$ | Maximum completion time |
| $e_{ij}$ | Ends setup time of $O_{ij}$ |
| $g_{ij}$ | Processing starts time of $O_{ij}$ |
| $h_{ij}$ | End processing time of $O_{ij}$ |
| $T_{ijk}$ | Processing time on machine $k$ of $O_{ij}$ |
| $P_{lk}$ | Transportation time from machine $l$ to $k$ |
| $W_{ijk}$ | Setup time on machine of $O_{ij}$ |
| $z_{ij}$ | For $O_{ij}$ 1 indicates that setup is required, 0 indicates that setup is not required |
| $x_{ijk}$ | For $O_{ij}$ 1 indicates that processing on machine $k$, 0 indicates not |
| $y_{ijkpq}$ | For$O_{ij}$ 1 indicates that processing before $O_{pq}$ on machine $k$, 0 indicates not |
| $L$ | A large positive number |
| $a$ | Virtual workpieces serve as start and end markers on the machine, helping to enforce tight-front and tight back constraints |

Based on the problem description, the model is constructed as follows:

$$mainCmax = maxC_i \tag{1}$$

$$h_{ij} \le v_{ij+1} \tag{2}$$

$$\sum_{k\in M} x_{ijk} = 1 \tag{3}$$

$$z_{ij} = \begin{cases} 1 \\ 1 - \sum_{k\in M}\sum_{p\in\{J_1,\dots,J_{j-1}\}} y_{ipkij} \end{cases} \tag{4}$$

$$h_{ij} = g_{ij} + \sum_{k\in M}\left(T_{ijk}\cdot x_{ijk}\right) \tag{5}$$

$$e_{ij} = s_{ij} + \sum_{k\in M}\left(W_{ijk}\cdot x_{ijk}\right)\cdot z_{ij} \tag{6}$$

$$u_{ij} = v_{ij} + \sum_{j,k\in M}\left(P_{ijk}\cdot x_{i(j-1)k}\right)\cdot x_{ijk} \tag{7}$$

$$h_{ij} \le s_{ij} + L\cdot\left(\sum_{k\in M} y_{ijkpq}\right) \tag{8}$$

$$\sum_{p\in J\cup\{a\},q\in J_p} y_{ijkpq} = x_{ijk} \tag{9}$$

$$\sum_{p\in J\cup\{a\},q\in J_p} y_{pqkij} = x_{ijk} \tag{10}$$

$$s_{ij} \le e_{ij} \le g_{ij} \le h_{ij} \le C_i \tag{11}$$

$$v_{ij} \le u_{ij} \le g_{ij} \le h_{ij} \le C_i \tag{12}$$

Eq. (2) stipulates those operations of the same job must be processed in sequence, and that transportation can commence only after the preceding operation is finished. Eq. (3) indicates that each process must be assigned to exactly one machine for processing. Eq. (4) indicates whether an operation requires setup. Eq. (5) represents the processing time constraints for the job. Eq. (6) represents the setup phase time constraints for the job. Eq. (7) represents the transportation phase time constraints for the job. Eq. (8) imposes timing constraints between adjacent operations and ensures that only one operation (whether setup or processing) can be performed on a machine at a time. Eq. (9) and Eq. (10) stipulate that if a job is being processed on a machine, there must be one preceding and one succeeding operation (including virtual operations). Eq. (11) and Eq. (12) represents the time constraints for each phase of the operation, requiring that the job must arrive at the machine and complete the setup before production begins. Additionally, the setup and transportation operations can occur independently.

## III. ALGORITHM DESIGN

The flexible job shop scheduling problem that considers both setup and transportation times, as investigated in this study, is an NP-hard problem. As the problem size grows, exact algorithms struggle to produce solutions within a short time. Considering the sparrow search algorithm's advantages—few parameters and ease of implementation—this study adopts and refines it to efficiently solve the aforementioned mixed-integer programming model.

### A. Encoding and Decoding

*1) In Flexible job shop scheduling research, encoding primarily addresses two aspects:* operation sequencing and machine selection. To address this challenge, a two-stage encoding scheme—operation sequence and machine sequence—is designed, as illustrated in Fig. 2.

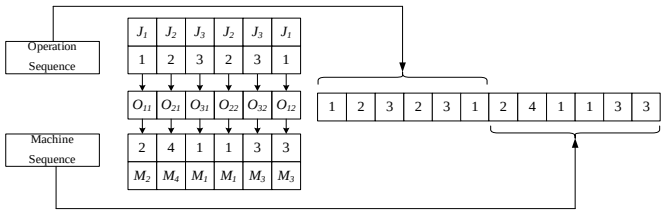



Fig. 2. An example of encoding.

*2) Operation Sequence (OS):* Each element in the sequence represents an operation for a job, and its position in the encoded sequence determines the order in which operations are performed. For example, if the OS sequence is1-2-1-3-2-3-1, it means the sequence of operations for these three jobs is $O_{11} - O_{21} - O_{12} - O_{31} - O_{22} - O_{32} - O_{13}$ .This encoding method

ensures the sequential constraints among multiple operations of each workpiece.

*3) Machine Sequence (MS): Each* element in the sequence represents a machine, specifying which machine processes the corresponding operation in the OS sequence. For example, if the MS sequence is 1-3-1-2-3-1-3, then $O_{11}$ is processed on machine $M_1$, and operation $O_{21}$ is processed on machine $M_3$.

By applying the Ranked Order Value (ROV) rule, one can map continuous individual vectors to discrete individual vectors. This process consists of two parts: encoding conversion for operation sequencing and encoding conversion for machine assignment. After decoding, one must evaluate the resulting machining scheme's quality and determine whether forward insertion of the workpiece is necessary.

- The operation sequence conversion steps are illustrated in Fig. 3.
- The machine encoding is mapped according to Eq. (13).

$$m_o = round\left(\frac{(\lambda+m)(m-1)}{2m} + 1\right) \quad (13)$$

The $o \in [1, d]$ represents the ordinal of the operation sequence, where $d$ is the total number of operations. The function, $round()$ performs rounding. The parameter $\lambda \in [-m, m]$ indicates that the coded position corresponds to the individual's location in continuous space. The variable $m$ denotes the total number of machines, and $m_o$ denotes the machine number selected for the corresponding operation $O_{ij}$.

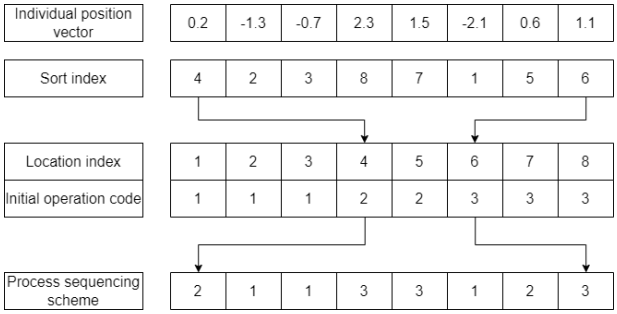



Fig. 3. ROV Mapping.

## B. Discoverers Location Update Strategy Optimization

An analysis of the discoverers' location update strategy in the sparrow population shows that when $R_2$ is lower than $ST$, the coefficient's range gradually shrinks from the initial [0,1] interval to roughly [0,1] as the number of iterations $i$ increases [16]. In particular, when $i$ is small, the coefficient is more l likely to be close to 1, thereby reducing the sparrow's range of activity in each dimension of the search space. Because finders constitute only a small fraction of the entire population, $i$ remains relatively small, causing the positional update factor to tend toward 1. To address this issue, if $R_2$ is less than ST, Eq. (14) can be used for the position update; otherwise, Eq. (15) is adopted.

$$X_{ij}^{t+1} = X_{ij}^{t} \cdot \left(2t + (-1)^t \cdot exp\left(\frac{-i}{a \cdot iter}\right)\right) \quad (14)$$

$$X_{ij}^{t+1} = X_{ij}^{t} + Q \cdot L \quad (15)$$

## C. Critical Path-Based Neighborhood Search

To further enhance the SSA algorithm's performance, a critical-path-based neighborhood search method is integrated into the basic SSA framework.

Processes located on the critical path often play a decisive role in determining the final quality of the overall scheduling scheme, as their completion times directly dictate the length of the entire production cycle. By adjusting these critical processes along with their adjacent operations, the algorithm explores additional solution spaces, thereby enhancing the potential to discover superior solutions. The procedure is as follows:

- Identify critical and non-critical operations;
- Randomly select one operation from the critical-operation set and one from the non-critical-operation set for swapping;
- New sequence feasibility check, the operation may be exchanged to the machine without processing capacity. The machine selection is carried out through the Earliest Completion Time First rule;
- Fitness calculation- Assign machines based on the workpiece coding sequence and machine coding, and perform forward insertion strategy to explore better results;
- Population update.

The pseudocode is as follows:

**Algorithm 1:** Critical path identification

```
Input: Operation Set
Begin:
    initialize CO
    for each operation O_ij:
        if h_ij = makespan then:
            put O_ij in CO
        end if
    end for
    while CO != null then:
        delete first operation O' of CO
        T = h_ij of O'
        for O_ij in Operation Set
            if h_ij = T then:
                put O_ij in CO
            end if
        end for
    end while
    return all marked operation
End
```

## D. Population Initialization

In the sparrow optimization algorithm, constructing the initial population is the first step, influencing the subsequent optimization process and outcomes. Although random initialization maintains the abundance and diversity of the population, the quality of individuals remains inconsistent. In

the initial phase of the algorithm, it may be difficult to quickly find a high-quality solution, requiring numerous iterations to gradually approach the optimal solution. This process raises the algorithm's computational cost and execution time. To enhance the algorithm's performance, this study employs random generation and ECT rule-based initialization to produce 50% of the population. The ECT rule dynamically calculates the completion time of each operation on every machine and assigns tasks to the machine with the earliest completion, thereby eliminating unreasonable machine selections during initialization and producing an initial solution that is both high in quality and diverse.

The pseudocode is as follows:

**Algorithm 2:** ECT rule

**Input:** Current operation ($O_{ij}$), process time on each machine ($T_{ijk}$), setup time on each machine ($W_{ijk}$), transportation time between $M_l$ (process$O_{ij-1}$) to current machine $M_k$($P_{lk}$)

**Begin:**
- **initialize** $t, p, w, completion\_time, et$
- **for** each machine$M_k$**:**
  - **If** $M_k$can process $O_{ij}$**then:**
    - $p = T_{ijk}, w = W_{ijk}$
    - **If** $O_{ij}$ is the first operation of the Job **or** the first operation on $M_k$ **or** $O_{ij}$ and $O_{pq}$ are from same job **then:**
      - $st = 0$
    - **end if**
    - **if** $O_{ij}$ is the first operation of the Job or $O_{ij-1}$ is processed on $M_k$ **then:**
      - $p = 0$
    - **else**
      - $p = P_{lk}$
    - **end if**
    - completion_time = $max(h_{ij-1} + tt, h_{pq} + w) + t$
    - **if** completion_time ≤ $et$ **then:**
      - mark current machine $M_k$ and update $et$
    - **end if**
  - **end if**
- **end for**
- **return** marked machine

**End**

## IV. Analysis of Numerical Experiments

This study performs an ablation experiment to validate both the effectiveness of the proposed algorithmic improvement strategy and the algorithm's overall efficiency. Additionally, small-scale and medium-to-large-scale experiments were conducted to further assess the algorithm's efficiency. The experiments were implemented in Java, running on an Intel(R) Core(TM) i5-7500 CPU @ 3.40GHz processor with 8GB RAM and the Windows 10 Professional operating system.

The experimental dataset consists of 15 newly created instances (MK01–MK10, Kacem01–Kacem05), which is generated by the small-scale Kacem dataset and the medium-scale Brandimarte dataset [18]. The commissioning time and shipping time are generated according to relevant strategies [19].

For the algorithm parameters, the population size exhibits a critical trade-off in optimization algorithms: an undersized population is prone to premature convergence to local optima, whereas an excessively large population imposes prohibitive computational overhead. Insufficient iteration cycles compromise convergence completeness while introducing substantial computational redundancy. The proportional allocation between discoverers and followers critically modulates the equilibrium between global exploration and local exploitation capacities within the algorithm framework. Through systematic orthogonal experimental design, the optimal parameter configuration was determined as follows: The population size was set to $N = 100$, the maximum number of iterations to $N\_iter = 400$, the discoverer proportion to $PD = 20\%$, and the vigilant proportion to $SD = 80\%$.

### A. Validation of the Improvement Strategy's Effectiveness

The Improved Sparrow Search Algorithm integrates three strategies into the standard algorithm: SSA1 denotes an optimized discoverer location update strategy, SSA2 represents population initialization via an ECT heuristic, and SSA3 adopts a critical-path-based neighborhood search strategy. This study designed eight sets of experiments to compare the strategies presented in TABLE II. The eight algorithms were each run independently ten times on the Brandimarte dataset, recording their best, average, and variance values, as well as the solution time.

TABLE II. Algorithm Comparison Strategy

| | SSA | SSA1 | SSA2 | SSA3 | SSA12 | SSA13 | SSA23 | SSA123 |
|---|---|---|---|---|---|---|---|---|
| Strategy 1 | ○ | ● | ○ | ○ | ● | ● | ○ | ● |
| Strategy 2 | ○ | ○ | ● | ○ | ● | ○ | ● | ● |
| Strategy 3 | ○ | ○ | ○ | ● | ○ | ● | ● | ● |

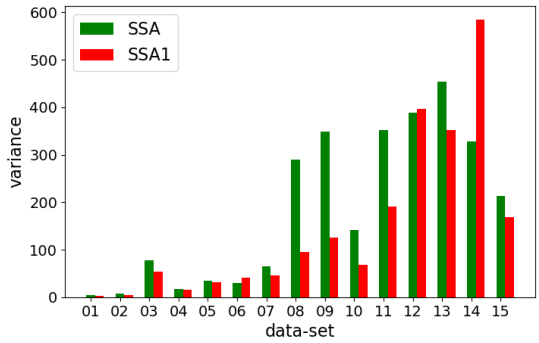
Note: ● indicates that the policy is applied; ○ indicates that the policy is not applied

*1) Analysis of the discoverer's location update strategy:* Strategy I modifies the parameters of the sparrow population's position update formula, increasing the step size and direction of the position update and enhancing the global search capability of the sparrow search algorithm to avoid local optima. In independent runs, the tenth solution comes closer to the optimum, showing reduced variance. As illustrated in Fig. 4(a), SSA1 outperforms SSA in variance across 12 of the 15 datasets, exhibiting a reduction of over 50% in Mk08 and Mk09. Fig. 4(b) to (d) presents comparative trials of the other groups incorporating Strategies II and III.

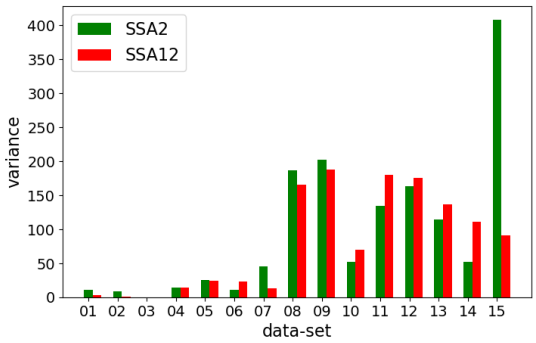
*2) Analysis of ECT rule strategies:* Among the four algorithms listed in Table II—SSA2, SSA12, SSA23, and SSA123—incorporate the finder location update strategy. To assess the impact of Strategy II, it is removed from these algorithms and compared with SSA, SSA1, SSA3, and SSA13. As a specific strategy, the ECT rule is tailored to the characteristics of this problem and is thus highly suited to the research in this chapter. The ECT rule quickly locates machines with shorter completion times, complementing the sparrow search algorithm. In conjunction with its global search

capability, this improves solution quality and efficiency. As shown in Fig. 5(a) to (d), when the effects of Strategies I and III are excluded, incorporating improved Strategy II yields superior solution quality. Since the sparrow algorithm relies on the current optimal solution when the sparrow population undergoes positional updating during the iterative process, high quality initial values can improve the solution quality. Results from ten independent experimental runs reveal a notable decrease in both the best and average values across all datasets, with a more pronounced effect on larger datasets. The quality of the initial population solution generated by the ECT rule and the random generation method is shown in Fig. 6(a), and the variance of the solution is shown in Fig. 6(b).

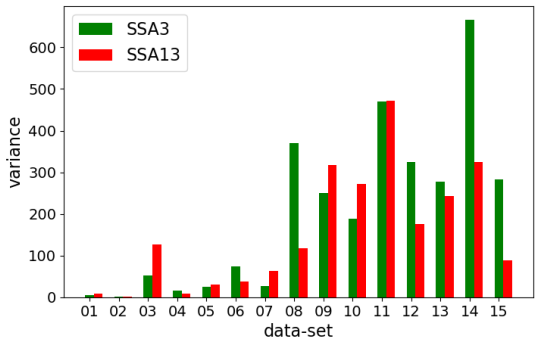
*3) Critical path-based neighborhood search strategy analysis:* Among the algorithms listed in Table II, SSA3, SSA13, SSA23, and SSA123 apply the location update strategy and culling Strategy II is compared with algorithms SSA, SSA1, SSA2, and SSA12. Incorporating Strategy III increases the solution time while reducing the average solution value. Since the processes on the critical path dictate the final completion time, each iteration later applies Strategy III to swap critical and non-critical processes. While this two-step operation of identifying and exchanging key processes increases computation time, it also enables a stronger local search capability. Fig. 7. (a) to (d) compares the effects of applying exclusion Strategies I and II and improvement strategy III on the algorithm's convergence performance. Incorporating Strategy III, clearly enhances the sparrow population's capacity for precise searching, leading to higher-quality solutions across iterations. The algorithm augmented by the improved Strategy III achieves an even better optimal solution.



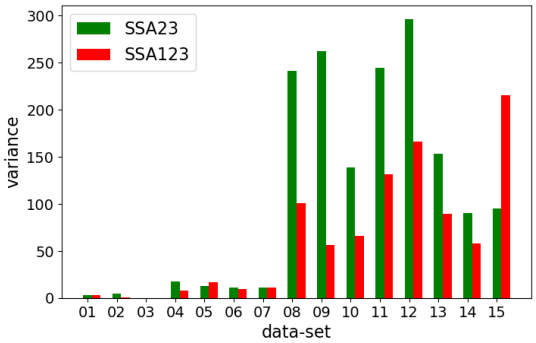

(a) Comparison of the variance of SSA and SSA1




(b) Comparison of the variance of SSA2 and SSA12

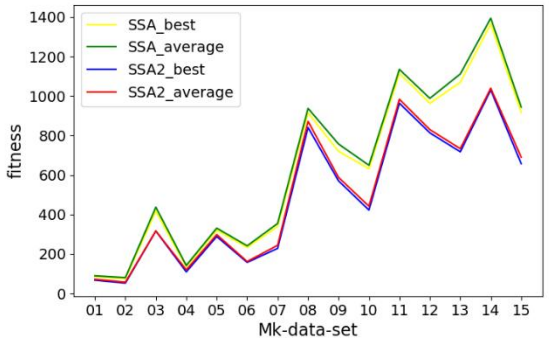



(c) Comparison of the variance of SSA3 and SSA13

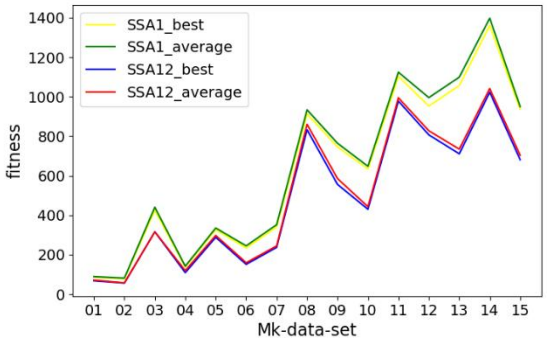



(d) Comparison of variance of SSA23 and SSA123

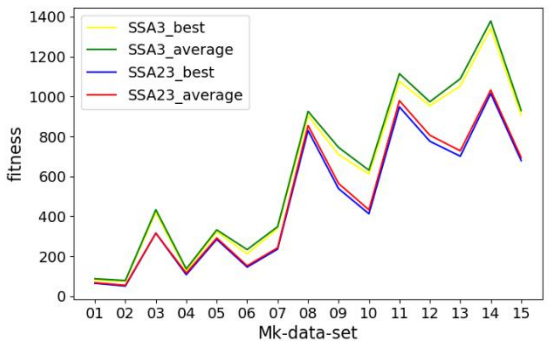
Fig. 4. Comparison of variance between algorithms with Strategy I.



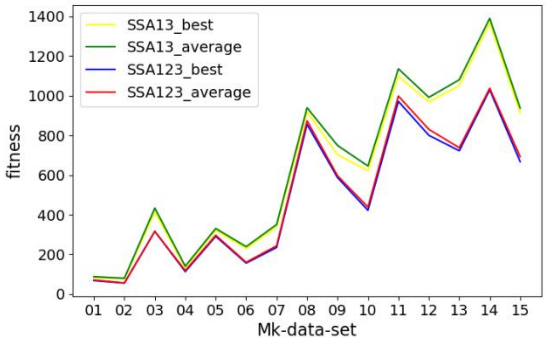

(a) Comparison of SSA and SSA2 results




(b) Comparison of SSA1 and SSA12 results

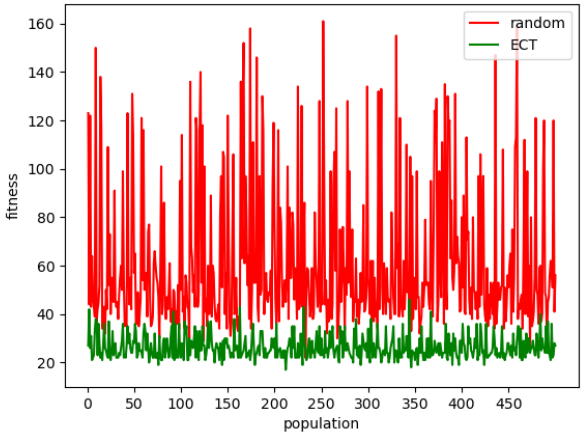



(c) Comparison of SSA3 and SSA23 results

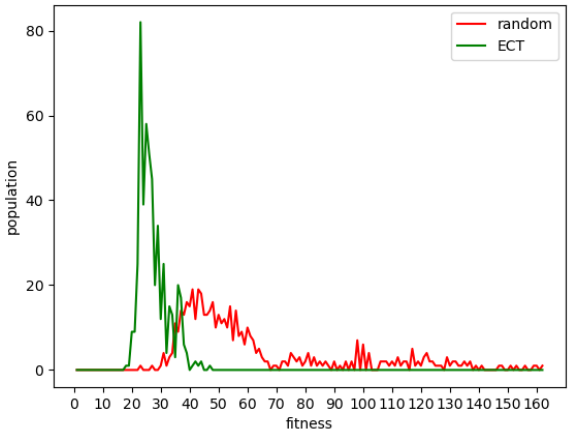



(d) Comparison of SSA13 and SSA123 results

Fig. 5. Comparison of fitness between algorithms with Strategy II.

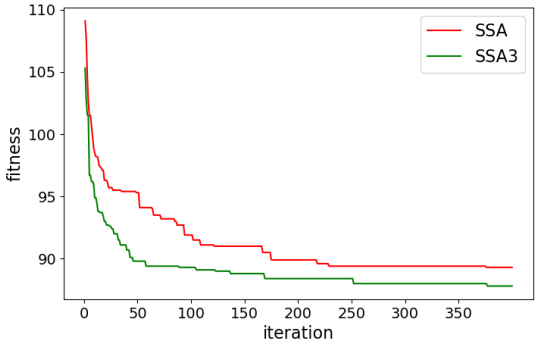



(a) Individual fitness of populations

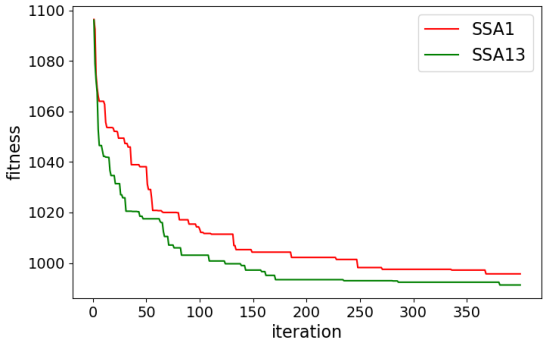



(b) Statistics on the fitness of the populations

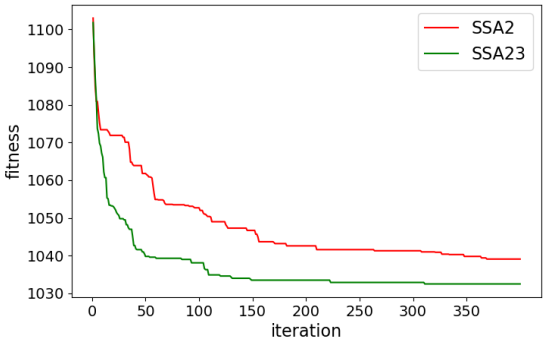
Fig. 6. Comparison of iterative process between algorithms with Strategy III.



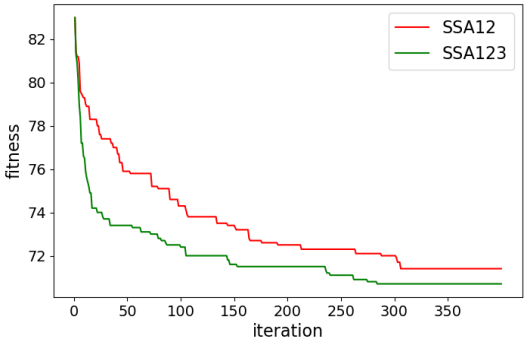

(a) SSA and SSA3 iterative process on Mk01




(b) SSA1 and SSA13 iterative process on Mk12




(c) SSA2 and SSA23 iterative process on Mk14




(d) SSA12 and SSA123 iterative process on Mk01

Fig. 7. Convergence under Strategies I-III; Strategies III shows improved precision and solution quality.

### B. Small-Scale Experimental Validation Analysis

In the small-scale experiments, Java was used to invoke the CPLEX solver for comparison with the Improved Sparrow Search Algorithm. The solution results for the small-scale Kacem benchmark instances are presented in TABLE III. The Improved Sparrow Search Algorithm's solution time grows slowly as the problem size increases. Moreover, the difference between its objective function value and that of the exact solution via CPLEX remains small—specifically, the gap between the optimal solutions is only 1. However, from the kacem8-8 instance onwards, ISSA runs significantly faster than the solver, demonstrating the effectiveness of the Improved Sparrow Search Algorithm.

TABLE III. COMPARISON OF CPLEX AND ISSA ON KACEM DATA SET

| Dataset | CPLEX | | ISSA | |
|---|---|---|---|---|
| | $f$ | $t/s$ | $f$ | $t/s$ |
| kacem4-5 | 16 | 0.22 | 17 | 3.63 |
| kacem8-8 | 22 | 32.03 | 24 | 10.61 |
| kacem10-7 | 17 | 322.98 | 18 | 9.97 |
| kacem10-10 | 11 | 37.13 | 12 | 11.11 |
| kacem15-10 | 22 | 115200 | 23 | 35.59 |

### C. Analysis of Large-Scale Experimental Validation

TABLE IV. presents the experimental results of the Improved Sparrow Search Algorithm compared with the standard sparrow search algorithm, the standard gray wolf optimization algorithm, and the genetic algorithm. The experiment uses the Brandimarte dataset, running each set of algorithms independently ten times. The average value was taken as the solution for each algorithm, and the performance gap between the three algorithms and the best solution among them was also recorded. From Table IV, it can be observed that the Improved Sparrow Search Algorithm shows a significant improvement in all 15 instances, with a minimum improvement rate of 7.96% and an average improvement rate of 26.48%. Moreover, the optimal values obtained by ISSA are consistently better than those achieved by the gray wolf algorithm and the genetic algorithm. The enhanced position updating strategy strengthens the sparrow search algorithm's global search capability, helping it avoid local optima and consistently discover superior solutions across all the 15 algorithms. In all 15 test instances, the Improved Sparrow Search Algorithm achieves the optimal solution. $G_g$ denotes the gap between the optimal values of the GWO, GA, and ISSA solutions. The GWO algorithm's smallest gap is 9.0%, with an average gap of 33%. Meanwhile, when comparing the GA algorithm to ISSA, the smallest gap is 20.3%, and the average gap is 56%. These findings confirm that the ISSA algorithm developed in this study exhibits superior stability, convergence, and efficiency when solving FJSP problems involving setup and transportation times.

TABLE IV. COMPARISON OF ISSA, SSA, GWO AND GA

| Dataset | ISSA | SSA | | GWO | | GA | |
|---|---|---|---|---|---|---|---|
| | $f$ | $f$ | $G_g$ | $f$ | $G_g$ | $f$ | $G_g$ |
| Mk01 | 70.7 | 84 | 18.81% | 91.0 | 28.7% | 92.3 | 30.6% |
| Mk02 | 56.0 | 75 | 33.93% | 83.1 | 48.4% | 77.1 | 37.7% |
| Mk03 | 316.0 | 416 | 31.65% | 439.4 | 39.1% | 543.7 | 72.1% |
| Mk04 | 118.2 | 135 | 14.21% | 141.2 | 19.5% | 154.9 | 31.0% |
| Mk05 | 296.4 | 320 | 7.96% | 341.6 | 15.2% | 358.5 | 21.0% |
| Mk06 | 160.1 | 233 | 45.53% | 246.1 | 53.7% | 332.3 | 107.6% |
| Mk07 | 243.4 | 339 | 39.28% | 362.2 | 48.8% | 321.1 | 31.9% |
| Mk08 | 873.4 | 914 | 4.65% | 952.0 | 9.0% | 1050.6 | 20.3% |
| Mk09 | 596.2 | 720 | 20.76% | 754.4 | 26.5% | 1051.6 | 76.4% |
| Mk10 | 438.2 | 631 | 44.00% | 652.2 | 48.8% | 918.2 | 109.5% |
| Mk11 | 997.6 | 1113 | 11.57% | 1145.1 | 14.8% | 1221.8 | 22.5% |
| Mk12 | 830.0 | 963 | 16.02% | 1010.0 | 21.7% | 1090.7 | 31.4% |
| Mk13 | 737.5 | 1069 | 44.95% | 1081.9 | 46.7% | 1427.8 | 93.6% |
| Mk14 | 1037.2 | 1364 | 31.51% | 1408.6 | 35.8% | 1602.1 | 54.5% |
| Mk15 | 692.4 | 917 | 32.44% | 952.8 | 37.6% | 1407.0 | 103.2% |

## V. RESULTS AND DISCUSSION

Firstly, the experimental validation presented in Section IV demonstrates that Strategy I effectively improves the algorithm's stability with better variance performance, while Strategy II significantly improves the quality of initial solutions, thereby accelerating the optimization process and elevating solution quality. Additionally, Strategy III achieves considerable improvements in both convergence speed and solution quality, with only a marginal increase in computational complexity.

Secondly, experimental results on small-scale instances show that the proposed algorithm produces solutions comparable to those obtained by CPLEX solver, while exhibiting superior computational efficiency. For small-scale problems, our algorithm can effectively generate production

scheduling solutions. In large-scale experiments, the proposed algorithm outperforms other classical algorithms in terms of both solution accuracy and quality, demonstrating its effectiveness in solving flexible job shop scheduling problems that consider both setup and transportation times.

## VI. CONCLUSION

Frequent production changes seriously impact the productivity of discrete order-driven manufacturing enterprises. This study considers the machine commissioning time caused by production changeovers and the transportation time due to workpiece changeovers on processing machines. A mixed-integer programming model is formulated to minimize the makespan, and an Improved Sparrow Search Algorithm is proposed to solve it. Experimental comparisons with CPLEX, the Gray Wolf Algorithm, and the Genetic Algorithm confirm the algorithm's effectiveness and efficiency. The results demonstrate that the location updating strategy involving an expanded search direction, the ECT-based population initialization tailored to the problem, and the critical-path-based neighborhood search strategy proposed herein significantly enhance both solution efficiency and quality for the sparrow search algorithm. Future research could refine this study by incorporating employee resource constraints in machine commissioning and the operation of transport equipment to address more complex flexible job shop scenarios.

Future studies will advance this work by integrating machine-setup constraints and operator resource limitations for material-handling equipment, thereby refining the scheduling model to accommodate more complex scenarios in flexible job shop environments.

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# A Hybrid Levy Arithmetic and Machine Learning-Based Intrusion Detection System for Software-Defined Internet of Things Environments

Wenpan SHI[1], Ning ZHANG[2]*
Department of Computer and Digital Law, Hebei Professional College of Political Science and Law, Shijiazhuang 050000, China[1]
Baoding Open University, Baoding 071000, China[2]

***Abstract*—The convergence of Software-Defined Networking (SDN) and the Internet of Things (IoT) has enabled a more adaptable framework for managing SDN-enabled IoT (SD-IoT) applications, but it also introduces significant cyber security risks. This study proposes a lightweight and explainable intrusion detection system (IDS) based on a hybrid Levy Arithmetic Algorithm (LAA) for SD-IoT environments. By integrating Levy randomization with the Arithmetic Optimization Algorithm (AOA), the LAA enhances feature selection efficiency while minimizing computational overhead. The model was evaluated using the NSL-KDD and UNSW-NB15 datasets. Experimental results demonstrate that the LAA outperformed baseline models, achieving up to 89.2% F1-score and 95.4% precision, while maintaining 100% detection of normal behaviors. These outcomes highlight the proposed system's potential for accurate and efficient detection of cyber-attacks in resource-constrained SD-IoT environments.**

***Keywords*—Intrusion detection; internet of things; software-defined; feature selection; levy arithmetic***

## I. Introduction

### A. Background

The Internet of Things (IoT) emerged from the rapid development of intelligent sensors recently and the need for device connectivity [1]. IoT presents broad opportunities in the healthcare, industrial, and supply chain industries, requiring robust stability, resilience, scalability, versatility, and control [2]. Moreover, IoT components have limits to their capabilities and contain embedded chips with various configurations. Traditional networks have become increasingly complex due to IoT-specific demands. Software-Defined IoT (SD-IoT) seeks to bring Software-Defined Networking (SDN) to the IoT by providing resource flexibility and network management for existing networks. SDN is considered a key technology to develop next-generation networks [3].

SDN transforms conventional Internet architecture via the separation of management and data layers [4]. Therefore, the management layer features more intelligence, programming, and innovation and accesses all SD-IoT components where resources and traffic can be efficiently managed. The security challenges associated with SD-IoT prevent its applications from being realized sooner. First of all, security concerns stem from the shared decision-making power of SD-IoT [5]. Attackers can quickly initiate and take over central controllers by conducting and applying malicious techniques and tactics like Denial of Service (DoS), Distributed DoS (DDoS), and malware, implement erroneous policies, and degrade network performance. Consequently, a security strategy must be a core part of the SD-IoT design to protect against cyber-attacks and maintain functionality [6].

### B. Problem Statement

A Network Intrusion Detection System (NIDS) is a tool developed to track and examine traffic on a network to identify threats, breaches, or illegal activities [7]. Signature-driven (also called misuse-focused or knowledge-based) and anomaly-based (also called behavior-based) methodologies are two primary methods for detecting intrusions into IoT systems [8]. It is possible to create a hybrid detection mechanism by combining both. However, this would require a lot of energy and resources to implement. Unlike anomaly-based systems that detect attacks based on traffic patterns, signature-driven systems classify traffic based on known threats. Existing and well-known attacks are well-protected by signature-based systems [9].

The rise of SD-IoT networks demands adaptive security mechanisms to address diverse cyber threats. While, commonly used, traditional methods like user authentication and encryption lack the flexibility to detect a wide range of evolving attacks in dynamic environments [10]. Intrusion Detection Systems (IDS), particularly those powered by machine learning, have proven effective in analyzing network traffic to identify attack patterns more accurately [11]. However, in resource-constrained SD-IoT systems, IDS models must be lightweight, analyzing only critical traffic features to maintain efficiency. Identifying these key attributes is a challenge. Moreover, ML-based IDS predictions are often tricky for cyber security experts to interpret, creating a need for Explainable Artificial Intelligence (XAI). XAI enhances transparency, allowing experts to understand and trust the decisions made by these models in cyber defense [12].

Applications such as geothermal energy extraction and underground mining increasingly rely on interconnected sensors and automated control systems for real-time monitoring and safety management. These cyber-physical environments, which include complex geological modeling and simulation efforts [13], are inherently vulnerable to cyber threats, thereby reinforcing the need for robust and lightweight intrusion detection systems in SD-IoT settings.

### C. Research Objectives

This study aims to address critical challenges in SD-IoT security by proposing an innovative solution for building a lightweight machine learning-based IDS. The main objective is to develop an efficient IDS by selecting an optimal subset of features, minimizing computational complexity, and conserving computing resources. The research introduces a novel feature selection method using the Levy-Arithmetic Algorithm (LAA), which applies the Levy flight random step theory to the Arithmetic Optimization Algorithm (AOA) to enhance search efficiency. Key contributions to this research include:

- Defining a security model for SD-IoT applications;
- Introducing a lightweight IDS using minimal features optimized by LAA;
- Training machine learning models such as Multi-Layer Perceptron, XGBoost, Random Forest, and Decision Tree on the selected features.

The remainder of the paper is structured as follows: Section II comprehensively reviews scholarly sources. Section III discusses the proposed method. Section IV presents the experimental setup and results. Section V outlines the primary outcomes, highlights the contributions, and suggests future research.

## II. Related Work

This section reviews the existing research on IDS for IoT deployments, listed in Table I. It highlights machine learning-based algorithms, feature selection techniques, and bio-inspired optimization algorithms for coping with resource constraints.

Rahman, et al. [14], proposed two approaches to overcome the limitations of centralized IDS for resource-limited endpoints: semi-distributed and decentralized. They used concurrent machine-learning algorithms to distribute the computing workload, with the semi-distributed scenario involving simultaneous modeling on the edge for feature selection and multiple classification layers. The decentralized scenario involved independent processes for feature selection and multi-layer perceptron classification, then amalgamated by a coordinated edge or fog for decision-making. The proposed approaches shows potential for detection accuracy equivalent to centralized IDS.

Forestiero [15], devised a technique for identifying irregularities in IoT using activity footprints. IoT2Vec, an embedding methodology, is used to depict devices and services using dense vectors. These vectors are allocated to mobile agents that adhere to an adapted bio-inspired paradigm. This approach facilitates intelligent global behavior derived from local movement rules recognized by all agents. A similarity rule facilitates each agent's selective application of movement rules, promoting automatic proximity among similar agents. The approach may detect solitary agents exhibiting anomalous behaviors, perhaps revealing intruders or malevolent users.

Li, et al. [16], used an Artificial Neural Network (ANN) to identify anomalous activity in a healthcare IoT system. The precision of recognition is significantly influenced by the characteristics inputted into the artificial neural network. Identifying relevant and distinctive aspects of network traffic is a critical and complex challenge due to its substantial influence on learning. The suggested approach utilizes the butterfly optimization algorithm to determine the ideal features for learning in an artificial neural network. The findings, achieving an accuracy of 92%, confirm the algorithm's efficacy in detecting discriminative aspects of traffic patterns. The suggested technique surpassed the performance of decision trees, support vector machines, and ant colony optimization used in prior research for the same objective.

TABLE I. Comparative Analysis of IDS Approaches for IoT Deployments

| Reference | Approach | Feature selection | Algorithm/model | Key findings |
|---|---|---|---|---|
| [14] | Semi-distributed and decentralized IDS approaches | Concurrent machine learning algorithms for workload distribution | Multi-layer Perceptron classification | Distributed IDS models show detection accuracy equivalent to centralized IDS. |
| [15] | Activity footprint analysis using IoT2Vec embedding | Bio-inspired selective movement rules | Mobile agents following adapted bio-inspired paradigms | The method detects anomalous behaviors by identifying isolated agents. |
| [16] | Anomaly detection in healthcare IoT | Butterfly optimization algorithm | Artificial neural network | Achieved 93.2% accuracy, outperforming decision trees, SVM, and ant colony optimization in feature selection. |
| [17] | Hybrid metaheuristic-deep learning for IoT intrusion detection | Harris hawk optimization and fractional derivative mutation | LSTM and GRU models | Outperformed other approaches in accuracy and efficiency on public datasets. |
| [18] | Detection of botnets using hybrid metaheuristics and machine learning | Modified firefly optimization | Hybrid CNN and quasi-recurrent neural network | Superior performance for botnet detection in cloud-based IoT systems. |
| [19] | IDS using variable searching pattern optimization for feature selection | Variable searching pattern optimization | Deep recurrent neural network | Achieved 96.1% accuracy, effectively identifying intrusions. |
| [20] | Hybrid IDS using grey wolf optimization and support vector machine | GWO for kernel function and parameter optimization | SVM with GWO | Outperformed other models in F-score, recall, precision, and accuracy on TON_IoT and NSL-KDD datasets. |

Sanju [17], presented a hybrid metaheuristic-deep learning methodology to improve the detection of intrusions in IoT systems. An enhanced metaheuristic approach using an ensemble of Recurrent Neural Networks (RNNs) is used to improve intrusion detection in IoT. Various attack kinds in IoT systems are discerned by using LSTM and GRU models, which are forms of RNNs. Feature selection is conducted using Harris Hawk optimization and fractional derivative mutation. The

evaluation of the suggested methodology used publicly accessible datasets, and the empirical study indicated that it outperforms other comparable approaches for accuracy and efficiency. It offers a viable technique for improving intrusion detection in IoT systems and may serve as a basis for future research in this domain.

Almuqren, et al. [18] introduced a Hybrid Metaheuristics with a Machine Learning-based Botnet Detection (HMMLB-BND) approach inside a cloud-assisted IoT system. HMMLB-BND concentrates on identifying and categorizing Botnet assaults inside the cloud-based IoT ecosystem. The Modified Firefly Optimization (MFO) algorithm is used for feature selection. HMMLB-BND employs a hybrid convolutional neural network and quasi-recurrent neural network module to identify botnets. The chaotic butterfly optimization approach is used for optimum hyperparameter tuning. A series of simulations were conducted on the N-BaIoT dataset, and the experimental results indicated the superiority of HMMLB-BND compared to other current methodologies.

Jayasankar, et al. [19] suggested an IDS using variable searching pattern optimization for feature selection with an optimum deep recurrent neural network model in an IoT context. It consists of a two-phase procedure: feature selection and incursion classification. In the first step, an ideal set of features is identified with variable searching pattern optimization. Subsequently, in the second phase, breaches are recognized and classified using the DRNN model. The hyperparameters of the DRNN are optimally selected using the Nadam optimizer. A comprehensive simulation study of the model is verified using a benchmark IDS dataset, and the results demonstrate the effectiveness of intrusion detection. The suggested model effectively identifies intrusions with an accuracy of 96.1%.

Ghasemi and Babaie [20] developed a hybrid intrusion detection technique using Grey Wolf Optimization (GWO) and Support Vector Machine (SVM). The SVM distinguishes between anomalous and normal records, while the GWO identifies the kernel function, selects features, and optimizes parameters for the SVM to enhance classification accuracy. The simulations demonstrate that the proposed method surpasses others in detection accuracy, precision, recall, and F-score on the NSL-KDD and TON_IoT datasets.

## III. Proposed Method

This section summarizes the graphical abstract used for the proposed model (LAA), which differs from conventional methods of selecting features. Detailed architectural pipelines for the model are described below. A methodology is described in the next section to elucidate the output (prediction) of the model. Fig. 1 illustrates a lightweight, explainable IDS.

This section presents a detailed method for determining appropriate features for devices with storage limitations. As a result, model performance improves owing to decreased calculation time and resource use. Machine learning relies on selecting a subset of optimum features from the available feature dimensions [21]. In this way, the dimensions of the feature vector become smaller, computation time decreases, and machine learning performance improves. A variety of feature selection techniques are used to reduce dimension. Some techniques for selecting features include LAA, information gain, and correlation coefficients.

AOA applies a metaheuristic strategy for analyzing exploration and exploitation balances based on math operations, like Addition, Subtraction, Multiplication, and Division. AOA is primarily inspired by the application of Arithmetic operators to resolve Arithmetic problems. According to Fig. 2, Arithmetic operators are arranged in a hierarchy according to their ascending dominance. The optimization procedure starts by randomly generating candidate solutions ($X$) given by Eq. (1). Best candidate solutions are considered the best-obtained or nearly optimum solutions in each iteration.

$$X = \begin{pmatrix} x_{1,1} & \cdots & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots & \cdots & x_{2,j} & \cdots & x_{2,n} \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ x_{n-1,1} & \cdots & \cdots & x_{n-1,j} & \cdots & x_{n-1,n} \\ x_{n,1} & \cdots & \cdots & x_{n,j} & x_{n,n-1} & x_{n,n} \end{pmatrix} \quad (1)$$

Prior to the AOA commencement, it must choose the search strategy (i.e., exploration or exploitation). The Math Optimizer Accelerated (MOA) function is a coefficient derived from Eq. (2) used in subsequent search stages.

$$MOA(C_{iter}) = Min + C_{iter} \times \left(\frac{Max-Min}{M_{iter}}\right) \quad (2)$$

where, $MOA(C_{iter})$ represents the value of the function at iteration *t*, $M_{iter}$ indicates the maximum number of iterations, $C_{iter}$ indicates the current iteration and *Min* and *Max* are the lowest and highest accelerated values.

In the AOA, the Division and Multiplication operators generate highly dispersed values during mathematical computations, enhancing the search process's exploration phase. However, due to their high dispersion, these operators struggle to converge on the target as efficiently as the Addition and Subtraction operators. The exploration phase focuses on identifying near-optimal solutions, often requiring several iterations. At this stage, Division and Multiplication operators play a key role in enhancing communication between the exploration and exploitation phases, ultimately supporting the search process.

AOA's exploration operators randomly scan the search space across different regions, aiming to identify better solutions using two primary strategies: the Division and Multiplication strategies, as represented in Eq. (3). This search phase is governed by the MOA function, with the condition r1 > MOA. As illustrated in Fig. 3, the Division operator is activated when r2 < 0.5, while the Multiplication operator remains inactive until the Division task is completed. If the condition is not met, the Multiplication operator takes over. A stochastic scaling coefficient is also applied to introduce more diversity into the exploration, ensuring that a broader range of regions within the search space is evaluated.

$$x_{i,j}(C_{iter}+1) = \begin{cases} best(x_j) \div (MOP+\varepsilon) \times \\ \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right), \quad r2 < 0.5 \\ best(x_j) \div MOP \times \\ \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right), \quad otherwise \end{cases} \quad (3)$$

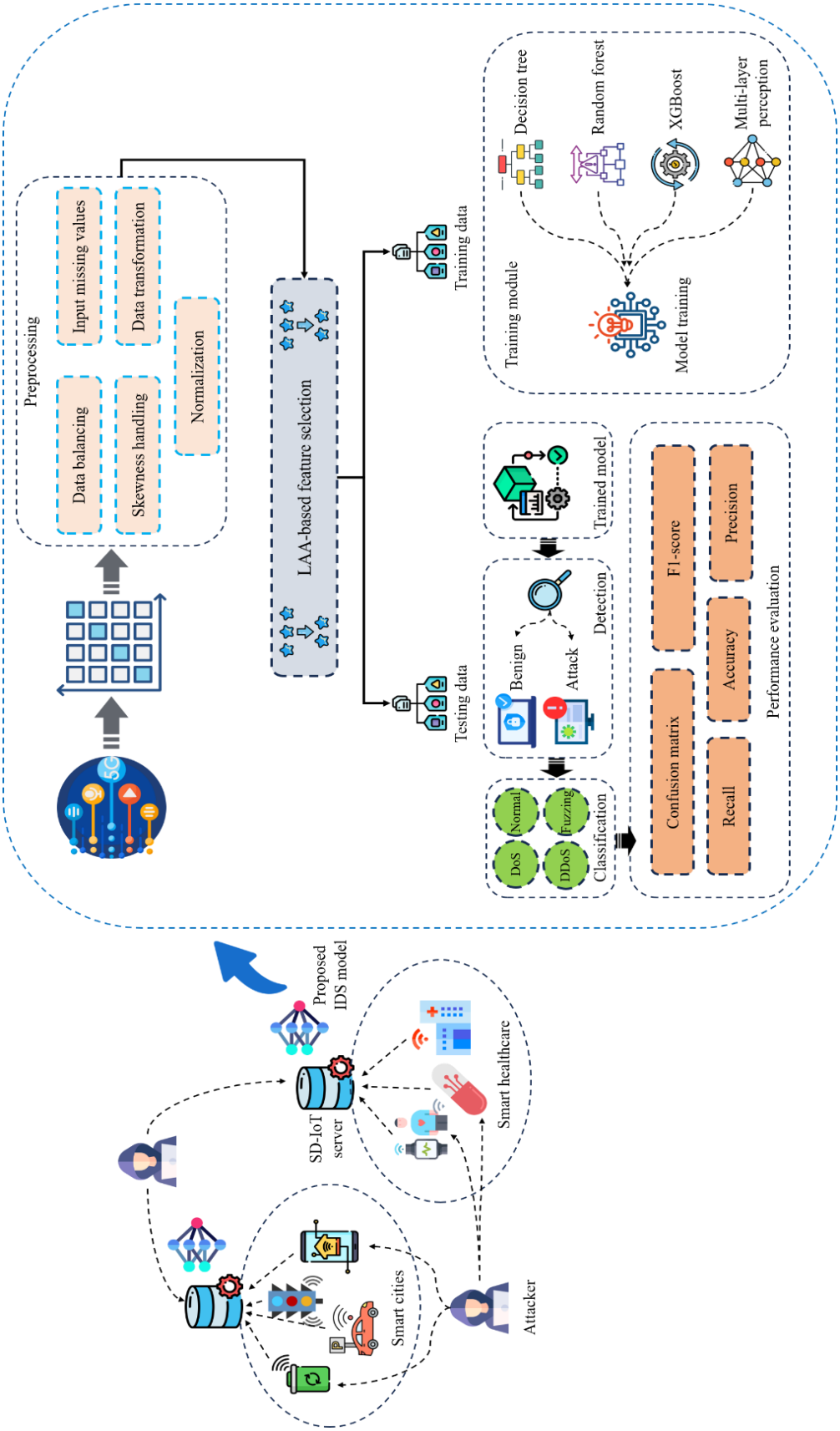


Fig. 1. System model.

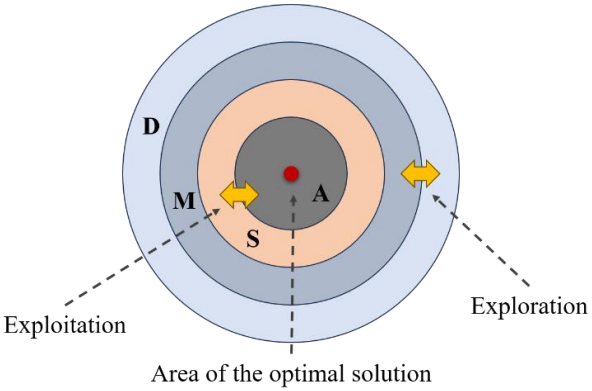


Fig. 2. Arithmetic operators.

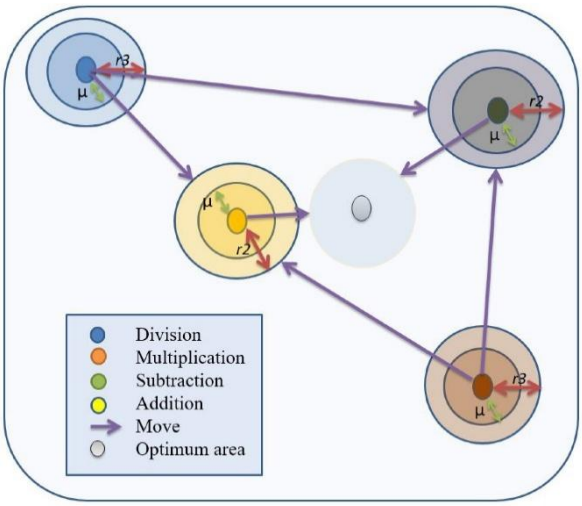


Fig. 3. Search space of AOA.

where, *r2* represents a random number ranging from 0 to 1, $\mu$ regulates search operations as a control parameter, $\varepsilon$ is a constant parameter for avoiding zero, and MOP gives a probability function-based math optimizer. Multiplication and subtraction operators have low precedence, allowing local searches to find the optimum outcome. The candidate solution is updated iteratively based on Eq. (4) to reach the optimal result.

$$x_{i,j}(C_{iter}+1) = \begin{cases} best(x_j) - MOP \times \\ \left((UB_j - LB_j) \times \mu + LB_j\right), & r3 < 0.5 \\ best(x_j) + MOP \times \\ \left((UB_j - LB_j) \times \mu + LB_j\right), & otherwise \end{cases} \quad (4)$$

In Eq. (3) and Eq. (4), Math Optimizer Probability (MOP) is the key function for finding the optimal value and determining its capability, determined by Eq. (5).

$$MOP(C_{iter}) = 1 - \frac{(C_{iter})^{1/a}}{(M_{iter})^{1/a}} \quad (5)$$

The Levy Random Step (LRS) denotes random walking in which the size of the steps follows a statistical distribution termed the Levy pattern. Its thick tails characterize this distribution, indicating that extreme or unusual events happen more often than normal occurrences. In a Lévy random walk, the step dimensions and orientations are sampled from this distribution, yielding many little steps interspersed with occasional significant leaps in random directions. This unpredictability must be regulated to successfully direct efforts toward optimum solutions while reducing departures from the best potential outcomes. Random steps are stochastic processes that involve taking a series of unpredictable steps, as expressed mathematically in Eq. (6).

$$S_n = \sum_{i=1}^{n} x_i = x_1 + x_2 + \cdots + x_n \quad (6)$$

where, $S_n$ is the sum of consecutive steps and $x_i$ represents each random step. The notion of Lévy random steps and flights, given by the French mathematician Paul Lévy, stems from the first investigations of stochastic processes in physics, including particle motion in fluids and gases. Levy walks and steps have been extensively studied and used across several disciplines, demonstrating their efficacy in optimization issues and other applications. The essence of a Lévy random step is rooted in the Lévy distribution, distinguished by its thick tails, which markedly enhance the probability of extreme step sizes relative to a normal distribution. The probability of a Lévy step may be mathematically estimated as shown in Eq. (7).

$$L(x) \approx |x|^{1-a} \quad (7)$$

where, α controls the tail heaviness, typically in the range $0<\alpha\leq 2$. The Levy distribution probability density function is expressed as in Eq. (8).

$$L(x) = \frac{1}{\pi}\int_0^{\infty} e^{-\gamma\tau^a} cos(\tau x) d\tau \quad (8)$$

where, $\gamma$ is a scaling parameter, usually set to 1, and $\tau$ is a small-time interval. As $\alpha$ increases, the distribution shifts closer to the mean, while lower values of $\alpha$ correspond to a distribution further from the mean. Mantegna's approach produces random numbers according to the Lévy distribution. This algorithm effectively generates Levy steps by sampling two random variables from normal distributions. The equation for producing Lévy steps is given in Eq. (9).

$$S = \frac{v}{|v|^{1/a}} \quad (9)$$

where, $v$ is a normally distributed variable, standard deviations $\sigma v$ determined by the Levy distribution's characteristics.

The LRS is advantageous in optimization algorithms as it facilitates rapid search space exploration via integrating both little, frequent steps and substantial, infrequent leaps. This dual nature enables the algorithm to evade local optima and progress toward more advantageous areas of the search space, hence increasing the probability of identifying a global optimum.

The fundamental components of metaheuristic algorithms, specifically the search space, assessment mechanism, position modification technique, new solution acceptance criteria, and stopping conditions, are crucial in determining their effectiveness. AOA is known for its simplicity and broad

applicability to various optimization problems. However, it may struggle with more complex problems, often getting trapped in local optima or requiring numerous iterations to reach the optimal solution. The AOA employs a math-optimized likelihood, as shown in Eq. (5), which adjusts iteratively and determines possible solutions within the search area, as described in Eq. (3) and Eq. (4).

To overcome these limitations, the proposed Levy Arithmetic Algorithm (LAA) introduces LRS into the AOA framework. By incorporating these steps, potential solutions can occasionally make broad, random shifts, allowing the algorithm to discover unexplored areas of the search domain and increasing the likelihood of discovering better optimal solutions.

In the LAA, candidate solutions are updated using the arithmetic operators from AOA and enhanced by the LRS, generating stochastic jumps based on the Levy pattern. This enables the solutions to shift randomly to new positions, promoting a more extensive search for optimal solutions in each cycle. The direction and scale of these jumps are influenced by decision variables (Dim) and population size (N), determined by the dimensionality of the problem and the characteristics of the LRS. While incorporating LRS allows for a broader search space exploration, it may be slower than the standard AOA to reach the optimum solution.

In LAA, the exploration phase, governed by Eq. (3), and the exploitation phase, defined by Eq. (4), are altered by LRS (*S*), as described in Eq. (9), and are expressed mathematically in Eq. (10) and Eq. (11).

$$x_{i,j}(C_{iter}+1)=\begin{cases} best(x_j)\div S\times(MOP+\varepsilon)\times \\ \left(\left(UB_j-LB_j\right)\times\mu+LB_j\right), \quad r2<0.5 \\ best(x_j)\times MOP\times S\times \\ \left(\left(UB_j-LB_j\right)\times\mu+LB_j\right), \quad otherwise \end{cases} \tag{10}$$

$$x_{i,j}(C_{iter}+1)=\begin{cases} best(x_j)-S\times MOP\times \\ \left(\left(UB_j-LB_j\right)\times\mu+LB_j\right), \quad r3<0.5 \\ best(x_j)\times MOP\times S\times \\ \left(\left(UB_j-LB_j\right)\times\mu+LB_j\right), \quad otherwise \end{cases} \tag{11}$$

using Eq. (10) and Eq. (11) enhances candidate solution diversity and prevents the algorithm from becoming stuck in local optima. By incorporating the LRS into the LA, the algorithm explores larger areas more effectively, thereby continuously discovering better solutions that traditional arithmetic optimization methods might miss. At first, fitness functions and best solutions are determined from objective functions, decision variables, and conditions, and they are dynamically modified based on the algorithm parameters and the potential solutions.

Three key variables (*r1, r2, r3*) are critical in narrowing the searching space based on four different operations: addition, subtraction, multiplication, and division, as defined by the Levy flight formulation, enabling the algorithm to approach the optimal solution. Integrating LRS enhances the algorithm's ability to search globally, making it more robust and efficient, thereby increasing the chances of identifying the global optimum. This method proves particularly useful in resolving optimization issues in which a number of local optima must be investigated before reaching the global best solution.

## IV. Results and Discussion

### A. Datasets

Two widely used datasets are used to analyze the proposed LAA for intrusion detection in SD-IoT environments: UNSW-NB15 and NSL-KDD. UNSW-NB15 is commonly used in intrusion detection research and contains 43 features, including primary network attributes and security features. It includes a class feature with several categories: Exploits, DoS, Fuzzers, Normal, and Backdoors. The dataset comprises 257,673 instances, 70% used for training and 30% for testing. NSL- KDD, as an improved version of the KDD Cup 1999 dataset, contains 42 attributes and focuses on four major types of attacks: Remote to Local (R2L), User to Root (U2R), DoS, and Probe. The dataset comprises 148,517 records, with 85% assigned to training and 15% for testing. Both datasets are significant for testing the efficiency of IDS models, as they cover a broad range of network traffic and cyber-attack scenarios, providing comprehensive benchmarks for assessing performance.

### B. Evaluation Metrics

The proposed LAA was assessed using a number of standard metrics, such as accuracy, precision, recall (true positive rate), and F1-score, commonly used in IDS research.

- Accuracy: This parameter determines the total correctness of the algorithm by evaluating the proportion of correctly classified instances relative to the total number of instances, calculated by Eq. (12).

$$A=\frac{\mathrm{TN}+\mathrm{TP}}{\mathrm{FN}+\mathrm{FP}+\mathrm{TN}+\mathrm{TP}} \tag{12}$$

where, FN is a false negative, FP is a false positive, TN is a true negative, and TP is a true positive.

- Precision: It determines the quality of positive predictions by multiplying the number of true positives by the number of positive predictions, calculated using Eq. (13).

$$P=\frac{\mathrm{TP}}{\mathrm{FP}+\mathrm{TP}} \tag{13}$$

- Recall: This metric represents the model's capacity to detect all positive instances correctly and is calculated using Eq. (14).

$$R=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{14}$$

- F1-score: Precision and recall can be balanced by a harmonic mean when data is imbalanced, as defined in Eq. (15).

$$F=2\times\frac{Recall\times Precision}{Recall+Precision} \tag{15}$$

### C. Environment

The experimental setup for evaluating LAA was performed on a system equipped with an Intel Core i5-8250U CPU running at 3.4 GHz with a Quad-Core configuration supported by 16 GB of DDR4 RAM. The operating system used was Windows 10 (64-bit), ensuring compatibility with the tools employed in the experiment. MATLAB was utilized to implement the LAA, while Python was used for data pre-processing and additional statistical analysis. This computational environment provided adequate resources to efficiently run the experiments, ensuring that the LAA's performance could be fairly compared with the baseline models in terms of speed and accuracy.

### D. Baseline Models

The effectiveness of LAA was evaluated by comparing it with well-established machine learning models of IDS. These included the SVM, which identifies the optimal hyper plane for classification tasks; Decision Tree (DT), which splits data based on feature values for decision-making; and Random Forest (RF), a method of constructing multiple decision trees to maximize accuracy and minimize over fitting. Additionally, models like ANN, which captures complex patterns in data, and Logistic Regression (LR), a simpler model estimating binary outcomes, were used. Other baseline models included K-Nearest Neighbors (KNN), a distance-based classifier; Naive Bayes (NB), a probabilistic model based on Bayes' theorem; and AdaBoost, a boosting technique that combines weak classifiers to form a more robust classifier. These models served as benchmarks to demonstrate how LAA compares accuracy, computational efficiency, and detection capabilities.

### E. Performance Evaluation

Fig. 4 shows the precision of the LAA and other algorithms for detecting intrusions in the UNSW-NB15 dataset. The LAA achieved the highest precision for several attack types, including Fuzzers (83.2%), Reconnaissance (85.5%), and Exploits (79.8%), while maintaining 100% precision for detecting normal behaviors. This high precision enhances the real-time performance of IoT systems, especially in hyper-automation processes. Although KNN and AdaBoost performed well in detecting Generic attacks with 100% precision, LAA's overall performance outpaced all other models. Fig. 5 demonstrates that in the NSL-KDD dataset, LAA delivered 95.4% precision, excelling at detecting anomaly attacks (Probe, DoS, U2R, and R2L), while DT achieved 93.1% and KNN reached 91.7%. Other models, such as LR and SVM, achieved precision scores of 90.2% and 89.6%, respectively.

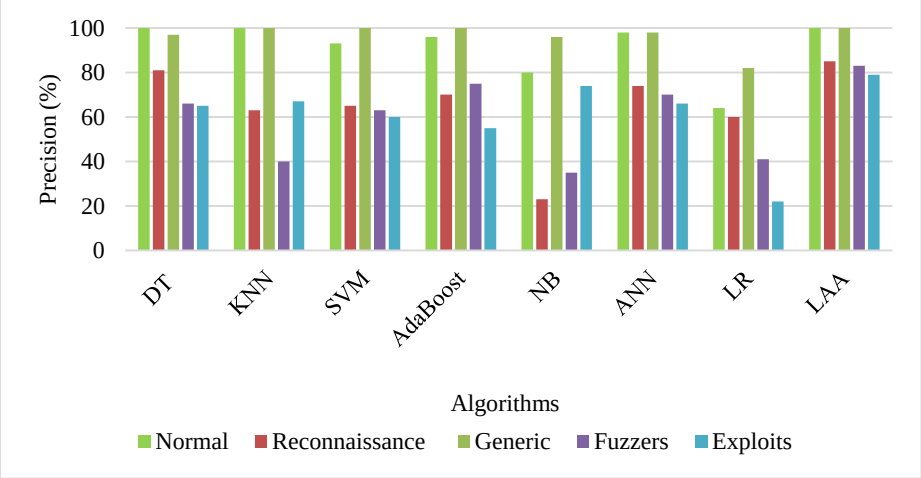


Fig. 4. Precision comparison under UNSW-NB15.

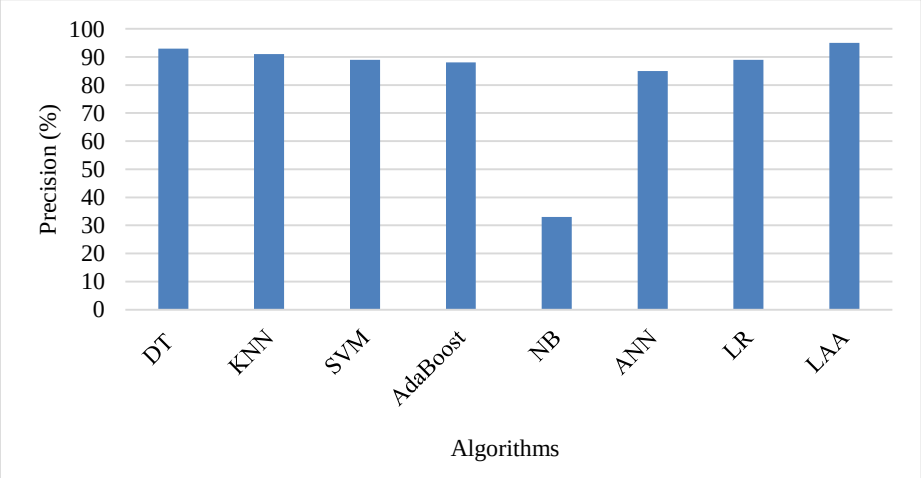


Fig. 5. Precision comparison under NSL-KDD.

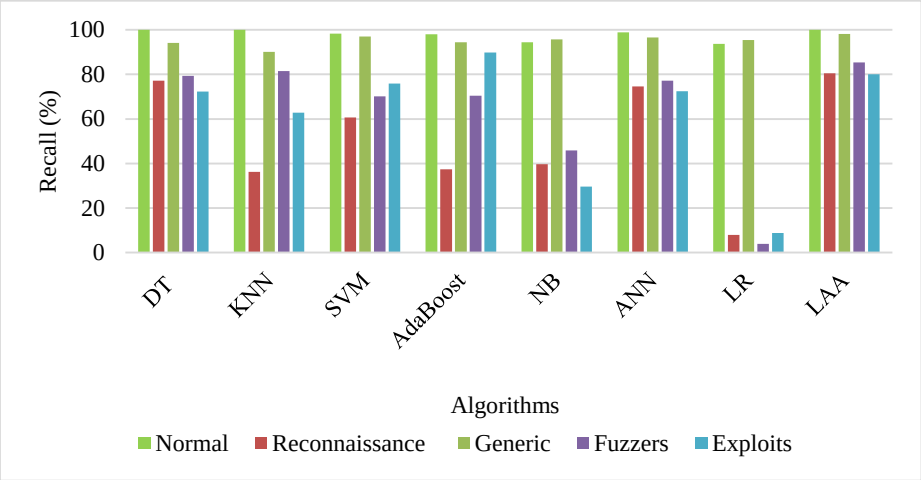


Fig. 6. Recall comparison under UNSW-NB15.

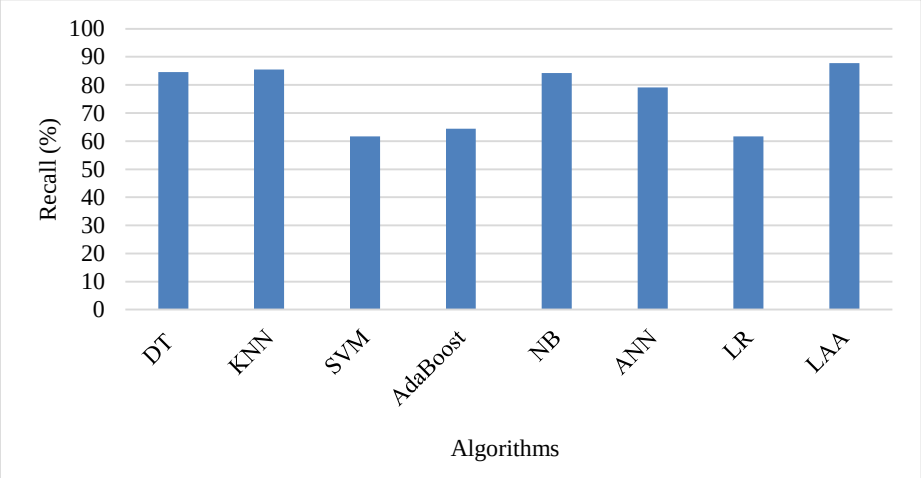


Fig. 7. Recall comparison under NSL-KDD.

Regarding recall, as depicted in Fig. 6, LAA outperformed other machine learning models in detecting cyber-attacks in the UNSW-NB15 dataset. Specifically, LAA achieved 85.4% recall for Fuzzers, 98.2% for Generic, and 80.5% for Reconnaissance attacks. The LAA also demonstrated 100% recall for detecting normal behaviors, ensuring high sensitivity in recognizing benign activities. In Fig. 7, LAA's recall in the NSL-KDD dataset stood at 87.8%, efficiently detecting anomaly categories such as Probe, DoS, U2R, and R2L. Comparatively, KNN achieved a recall of 85.5%, DT reached 84.6%, and NB provided 84.3%. Lower recall values were recorded for models like AdaBoost (64.4%) and SVM (61.7%).

Fig. 8 and Fig. 9 compares the F1-score across different algorithms for both datasets. In the UNSW-NB15 dataset, the LAA attained the highest F1-score of 87.4%, surpassing models such as ANN (83.2%), AdaBoost (82.2%), and SVM (78.9%). Other algorithms like DT (75.8%), KNN (74.1%), and NB (60.7%) recorded lower F1-scores, highlighting the superior performance of the LAA. For the NSL-KDD dataset, LAA again led with an F1-score of 89.2%, while DT and KNN followed with 88.5% and 87.3%, respectively. Models like ANN, LR, and SVM lagged with F1-scores of 82.1%, 73.2%, and 73.1%, respectively. NB exhibited the lowest F1-score at 46.2%.

These findings are consistent with recent studies that emphasize the importance of hybrid optimization in IDS performance. For example, the model proposed by Sanju [17], which integrates metaheuristics with deep learning, also demonstrates competitive F1-scores; however, our method achieved higher precision and recall across both datasets. Similarly, the approach by Almuqren, et al. [18] using Modified Firefly Optimization for botnet detection shows high performance, yet lacks the lightweight and explainable characteristics emphasized in our LAA framework. Compared to the SVM–GWO hybrid by Ghasemi and Babaie [20], our model achieved superior accuracy and a more balanced F1- score, particularly in detecting diverse attack classes under constrained environments.

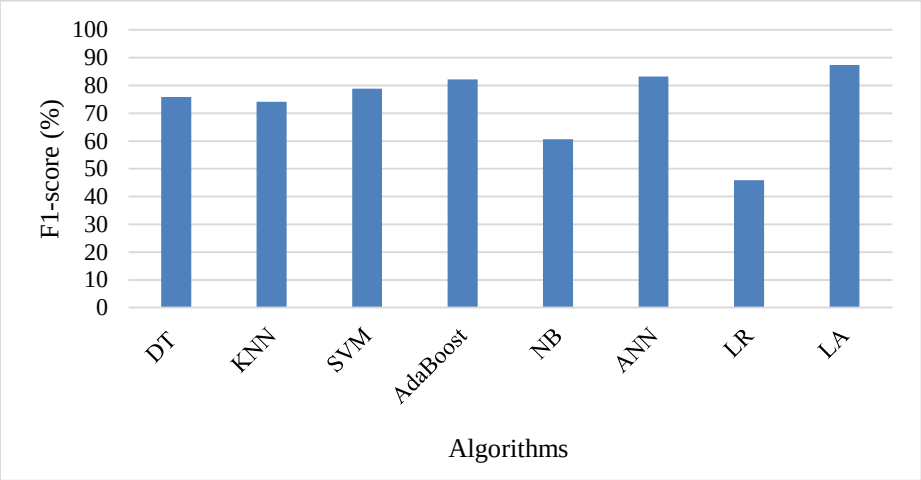


Fig. 8. F1-score comparison under UNSW-NB15.

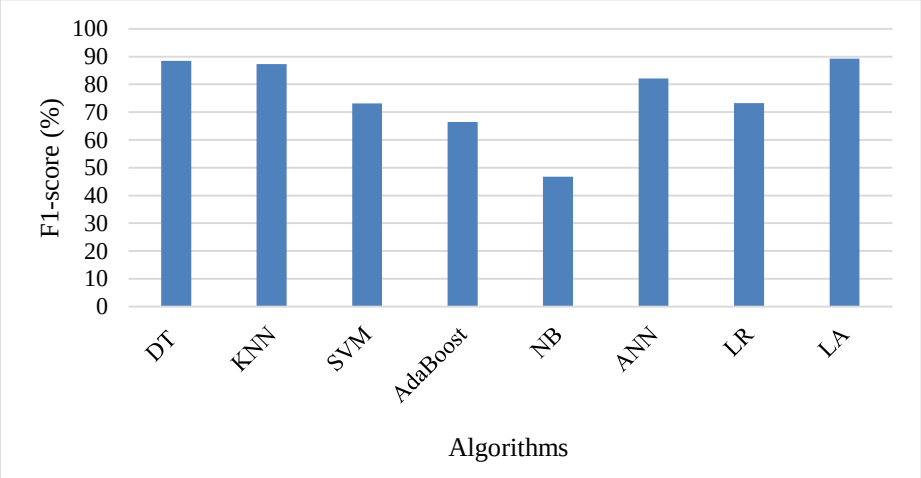


Fig. 9. F1-score comparison under NSL-KDD.

## V. Conclusion

In this study, we introduced LAA as a novel and efficient method for enhancing intrusion detection in SD-IoT environments. By integrating LRS with the AOA, the LAA achieved a more dynamic balance between exploration and exploitation, efficiently navigating complex search spaces and identifying optimal solutions for feature selection. The experimental results on the NSL-KDD and UNSW-NB15 datasets demonstrated that the suggested LAA-based IDS model outperformed conventional machine learning algorithms in key performance indicators such as F1-score, recall, precision, and accuracy. The LAA's ability to achieve high detection rates while maintaining computational efficiency makes it particularly well-suited to resource-constrained SD-IoT systems. The proposed LAA presents a significant advancement in intrusion detection, providing a robust, lightweight, and explainable solution for detecting cyber-attacks in SD-IoT environments.

Despite these promising results, the study has certain limitations. First, the performance of the LAA is somewhat dependent on the fine-tuning of algorithmic parameters, which may require domain-specific expertise. Second, although benchmark datasets such as NSL-KDD and UNSW-NB15 ensure comparability, the model's effectiveness on real-world, heterogeneous SD-IoT traffic remains to be assessed. Finally, while the method is computationally efficient in experimental settings, its scalability and real-time performance under production-scale environments require further validation. Future work can explore the extension of LAA to other IoT applications and networks, as well as the development of more advanced hybrid models to further improve detection rates and reduce computational costs.

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# Reinforcement Learning-Driven Cluster Head Selection for Reliable Data Transmission in Dense Wireless Sensor Networks

Longyang Du*, Qingxuan Wang, Zhigang ZHANG
School of Artificial Intelligence, Jiaozuo University, Jiaozuo 454000, Henan, China

***Abstract*—Wireless Sensor Networks (WSNs) have made significant advances towards practical applications. Data gathering in WSNs has been carried out using various techniques, such as multi-path routing, tree topologies, and clustering. Conventional systems lack a reliable and effective mechanism for dealing with end-to-end connection, traffic, and mobility problems. These deficiencies often lead to poor network performance. We propose an Internet of Things (IoT)-integrated densely distributed WSN system. The system utilizes a tree-based clustering approach dependent on the installed sensors' density. The cluster head nodes are structured in a tree-based cluster to optimize the process of gathering data. Each cluster's most efficient aggregation node is selected using a fuzzy inference-based reinforcement learning technique. The decision is based on three crucial factors: algebraic connectedness, bipartivity index, and neighborhood overlap. The proposed method significantly enhances energy efficiency and outperforms existing methods in bit error rate, throughput, packet delivery ratio, and delay.**

***Keywords*—Energy efficiency; wireless sensor networks; clustering; reinforcement learning; fuzzy inference system**

## I. INTRODUCTION

### A. Overview

Wireless Sensor Networks (WSNs) represent a paradigm shift in global technological scenarios and consist of many autonomous sensor nodes capable of carrying out extensive sensing, computation, and communication [1]. Through strategic deployment, WSN nodes reside in a wide range of environments [2]. WSNs constitute a fundamental infrastructure that enables computing systems to gather data, process, and transmit it in real-time from the physical world [3]. This pervasive connectivity opens up applications for numerous fields, such as environmental monitoring, medical care, manufacturing, and sustainable communities [4], [5].

The collaborative nature of sensor nodes within WSNs enables the creation of distributed systems capable of collecting and relaying useful information on environmental parameters, object movement, health indicators, and other relevant data [6]. The inherent characteristic of WSNs, which can be modified to accommodate dynamic and adversarial environments, allows the generation of actionable intelligence, enhancing decision-making processes and improving situational awareness [7], [8].

Like constitutive models, which model the behavior of weak rock masses under different states of stress, taking into account pore pressure and temperature [9], WSNs must combine several environmental parameters to achieve optimal data collection and network operation. Yet, the deployment and operation of WSNs also entail inherent constraints, such as energy limitations [10], scalability issues [11], data security concerns [12], and network reliability [13], which demand innovative solutions and algorithms that ensure optimal performance and overcome these constraints. Despite these concerns, WSNs are a fundamental technology that drives innovation, revolutionizing businesses and enhancing our understanding of the world [14].

### B. Motivation and Contribution

Several methodologies have been proposed, encompassing diverse techniques such as multi-path routing, tree structures, clustering, and cluster trees, yet they often struggle to ensure a robust and reliable system addressing mobility, traffic dynamics, and end-to-end connectivity individually [15-17]. Consequently, these shortcomings frequently lead to suboptimal network performance, hindering their full potential in practical applications. To solve these challenges, this study introduces a novel scheme tailored to a densely distributed WSN system model.

With a tree-based cluster formation strategy, a flexible deployment density for sensor nodes is accommodated under this innovative framework. Each cluster in this meticulously structured architecture is meticulously organized around a singular cluster head node, a design crafted to streamline and optimize energy-efficient data-gathering processes. A distinguishing element in this scheme is incorporating a fuzzy logic engine and reinforcement learning. This sophisticated system dynamically determines optimal data-gathering nodes within clusters embedded within a densely distributed WSN. This decision-making process requires the evaluation of three key metrics: algebraic connectivity, bipartivity index, and neighborhood overlap.

The proposed approach intelligently assigns data collection tasks, promoting efficiency and energy savings in the network. Like machine learning techniques, such as regression and clustering algorithms, assist in analyzing the effects of various factors on business economics [18], this approach enables effective data-driven decision-making for optimizing resource usage and improving network performance. This study has made the following primary contributions:

- Advanced multi-cluster data collection: We introduce a novel multi-cluster data collection strategy tailored for

densely distributed WSNs, addressing the complexities of large-scale monitoring applications.

- Cluster formation based on energy and delay factors: We propose a robust approach to select cluster heads within each cluster, leveraging energy and delay factors to optimize the network's performance for lifespan, throughput, packet delivery rate, and reliable links for mobile sensors.
- Reinforcement Learning-based Fuzzy Logic Engine (RL-FLE): We use incorporated RL-FLE for intelligent decision-making, empowering cluster heads to dynamically determine optimal data-gathering nodes based on link efficiency among neighboring nodes.
- Improved performance indicators: The proposed approach demonstrates superior performance over traditional protocols (LEACH, HEED, MBC) by maximizing link stability and enhancing critical performance indicators, including packet delivery rate, bit error rate, end-to-end delay, and throughput.
- Reduced buffer occupancy and network traffic: Our proposed scheme effectively reduces buffer occupancy and minimizes network traffic, verifying its efficiency in managing data flow and ensuring resource optimization compared to existing protocols.
- Potential for energy savings: Experiments reveal the potential for substantial energy savings, emphasizing the energy-efficient nature of the proposed approach for sustainable and long-term network operation.

The study is structured as follows: Section II reviews related research. Section III presents the methodology, detailing the approach, algorithms, and framework used in the study. Section IV analyzes the findings, comparing them with existing studies and discussing their implications. Finally, Section V summarizes the key insights, highlights the contributions, and suggests potential directions for future research.

## II. Related Works

Table I summarizes methodologies, key contributions, evaluation metrics, and results from related works concerning data collection, energy efficiency, and network optimization.

TABLE I. Overview of Recent Routing Protocols

| Reference | Methodology | Key contributions | Results |
|---|---|---|---|
| [19] | Secure mobile sensor network with cloud integration | Optimizing performance through efficient routing, energy consumption, and security enhancement. Lightweight and congestion equilibrium-focused data collection scheme. Transmission facilitated via AND-OR graph mechanism. Secure access to collected data for cloud computing. | Significant energy savings and enhanced network stability |
| [20] | Rechargeable WSNs | Far-relay approach for proportional energy consumption. Optimal scheduling with Opt-JoDGE. Buffer-battery-aware adaptive scheduling with NO-BBA. | NO-BBA closely approaches Opt-JoDGE performance, especially in scenarios with acceptable delay levels. |
| [21] | Data gathering in WSNs with obstacles | Cluster construction with ant colony optimization and hierarchical aggregation. MS tour formation with multi-agent reinforcement learning and Cluster construction with ant colony optimization and hierarchical aggregation. | DGOB addresses energy consumption and data gathering delay challenges in WSNs with obstacles. |
| [22] | Trust-aware and energy-efficient data gathering | Clustering, tree construction, and watchdog selection with particle swarm optimization. Variable-length particles for the unknown number of watchdogs. | TEDG algorithm significantly improves energy efficiency and extends network longevity. |
| [23] | RLSSA-CDG for energy efficiency in WSNs | RLSSA-CDG combines CDG with sleep scheduling in a distributed algorithm. Q-learning algorithm for active node selection. | RLSSA-CDG outperforms other algorithms, demonstrating its energy efficiency and superiority in network lifespan extension. |
| [24] | Clustering with mobile data collector | Mobile data collector traverses the network for effective data collection. | An optimized approach to mobile data collection, demonstrating effectiveness in both balanced and unbalanced network topologies. |
| [25] | Energy-aware and cluster-based data aggregation | Fuzzy logic and CapSA for clustering and routing. | CEDAR performs better than prior research in delay, packet delivery rate, and network lifespan. |
| [26] | Multi-channel design for high throughput in WSNs | Utilizes a subset of cluster heads with multiple radios. Genetic algorithm for clustering, routing, and channel assignment. | It achieves a significant increase in throughput, reduced energy consumption, and improved energy utilization compared to previous schemes. |

The increasing utilization of lightweight sensors has driven the advancement of emerging technologies in various domains. One notable trend is integrating cloud services in applications that handle large volumes of observational data. However, the dynamic and time-sensitive nature of these environments requires enhanced performance. Eco-friendly systems require stable and reliable data transmission. Additionally, many green network solutions are vulnerable to unforeseen situations resulting from broadcasting on unreserved mediums.

To meet the mentioned demands, Haseeb, et al. [19], have introduced a secure mobile sensor network that integrates cloud technology to optimize performance through efficient routing, energy consumption, and security enhancement. Their work

makes significant contributions in several aspects. Firstly, it focuses on establishing a stable and error-free system for collecting data from mobile sensors to reduce unnecessary energy usage. The proposed data-gathering method is lightweight and maintains congestion equilibrium. An AND-OR graph mechanism facilitates green data transmission from mobile data sources to the cloud, which reduces routing gaps and retransmissions. Cloud computing can provide secure access to the collected data from constraint-oriented green environments.

Liu, et al. [20], studied energy harvesting and joint data gathering challenges in battery-powered WSNs by employing mobile sinks. As a mobile sink travels along a predetermined route, sensor nodes harvest energy from its RF circuits. Meanwhile, these nodes relay sensor data to the sink. A far-relay strategy is proposed to address the proportional relationship between energy consumption and energy harvesting at a sensor node, determined by the distance squared among sensor nodes. This strategy aims to choose sensor nodes near the path to facilitate data transmission to nodes located at a greater distance. The far-relay technique involves formulating a network utility maximization issue and introducing an optimum scheduling strategy considering time slot scheduling, relay selection, and power allocation regulations.

To tackle the issue of effectively managing sensor power and minimizing the delay in capturing data, mainly when obstacles are present, Najjar-Ghabel, et al. [21], have introduced DGOB, which gathers data in WSNs with obstacles. DGOB employs node clustering and a mobile sink to collect cluster heads' data, minimizing network energy usage. The algorithm follows a two-phase process: cluster construction and mobile sink tour formation. DGOB employs two methods to create superior clusters in the cluster construction phase. The first phase involves the combination of hierarchical aggregation with ant colony optimization to produce resilient clusters under adverse conditions. In the subsequent iterations, the Genetic Algorithm (GA) updates the current clusters, thus improving the cluster development process. In the second stage, DGOB presents a proficient approach to constructing tours by combining multi-agent reinforcement learning and GA. The success of DGOB is confirmed by comprehensive simulation findings, demonstrating a 34 per cent reduction in energy usage and an 80 per cent increase in network longevity compared to existing techniques.

Soltani, et al. [22], have presented a trustworthy and energy-aware data aggregation algorithm to enhance data collection efficiency in WSNs. It consists of several vital stages, namely clustering, tree formation, and watchdog determination, each framed as an optimization problem and optimized by the Particle Swarm Optimization (PSO) algorithm. The watchdog selection stage can be particularly noteworthy as it involves particles of variable length due to the unknown number of watchdogs. To address this challenge, a new particle representation and initialization scheme is developed. The proposed algorithm has demonstrated significant improvements in performance metrics through extensive simulations. It significantly improves energy efficiency in delivering data to the sink node, decreases nodes' residual energy standard deviation by 81per cent, and extends the network's lifespan to 129per cent.

Wang, et al. [23], have introduced the Reinforcement Learning-based Sleep Scheduling Approach for Compressed Data Collection (RLSSA-CDC) to enhance energy efficiency in WSNs. This algorithm combines Compressive Data Collection (CDC) with sleep scheduling to reduce data transmission and minimize energy consumption in WSNs. Unlike previous approaches that faced challenges with centralized optimization problems and increased control message exchanges, RLSSA-CDC is formulated as a distributed algorithm. This framework minimizes control message exchanges and adapts to the variance in residual node energy, preventing nodes from premature energy depletion.

Meddah, et al. [24], suggest a novel strategy to mitigate energy waste in WSNs by utilizing Mobile Data Collector (MDC) devices. An MDC device collects data efficiently from sensor nodes by traversing the network. Their proposed method, called the Tree Clustering algorithm with MDC, aims to establish an optimized traveling path through a subset of cluster heads while minimizing the travel distance. The cluster heads are chosen by a competitive selection system that considers several factors, including packet transmission rate, closeness to the root of the tree, node energy level, and proximity to the next cluster head. The efficacy of the suggested approach was evaluated using simulation tests done on both balanced and unbalanced network topologies.

Mohseni, et al. [25], developed a Clustered Energy-conscious Data Aggregation Routing protocol called CEDAR, incorporating a fuzzy logic model and Capuchin Search Algorithm (CapSA). It comprises two steps: cluster creation and extra/intra-cluster routing. Initially, sensor nodes are clustered using fuzzy logic. Then, CapSA determines optimal paths between cluster heads, the base station, and cluster nodes. As demonstrated by the simulations conducted in the MATLAB simulator, CEDAR is superior to existing research concerning packet delivery rate, latency, and network lifetime.

Shahryari, et al. [26], have addressed high-throughput WSN requirements by implementing the multi-channel framework designed explicitly for heterogeneous WSNs. This approach aimed to overcome the limitations present in existing multi-channel methodologies, which often suffer from low throughput and significant overhead. Their innovative solution introduced a paradigm that utilized a subset of high-level nodes, known as cluster heads, with multiple radios within the network. These cluster heads efficiently transfer captured data from standard sensors to the base station. To achieve this, an energy-saving and high-throughput algorithm was developed to manage routing, clustering, and channel assignment processes in this diverse WSN setup.

The first stage focused on forming a spanning tree among the super nodes while intelligently determining appropriate channels for their radios. They introduced a novel multi-objective cost function extending the network lifetime over conventional tree construction methods. Additionally, this function effectively manages interference, improving overall throughput across the network. In the subsequent stage, the

algorithm determined the optimal selection of cluster heads and channels for standard nodes. Their algorithm demonstrated a substantial increase in throughput through extensive simulations due to multiple channel utilization. Moreover, it achieved notable reductions in energy consumption per transmitted bit to the base station, achieving an impressive improvement of 21.6 per cent and 48.3 per cent, respectively, compared to prior schemes.

## III. PROPOSED METHOD

The mobile sink-centric information collection approach prevalent in densely distributed WSNs often consumes more energy by sensor nodes closer to the sink node, leading to energy holes. Existing Expectation Maximization (EM)-based clustering approaches have attempted to mitigate this problem by optimizing the number of clusters to minimize energy consumption. However, these approaches struggle to determine cluster heads effectively, especially as the scale and node density of the network increase, resulting in increased energy consumption and shorter network lifetime. To meet these challenges, this study presents a novel tree-based clustering scheme supported by robust cluster heads to prolong network lifetime and improve energy efficiency.

A single cluster head node controls each cluster to ensure efficient information collection. First, RL-FLE determines strong cluster heads within clusters of densely distributed WSNs. This determination relies on three key variables: neighborhood coverage, mathematical connectivity, and bipartivity index. Then, dynamic network reconfiguration is performed by moving the sink to a different position and consolidating the cluster head node when node failures occur in a cluster. This adaptive framework is expected to prolong network lifespan and minimize energy usage. The effectiveness of the suggested strategy is determined through a comparative analysis of existing methods.

A static and energy-efficient routing scheme is introduced for the complex and diverse IoT ecosystem. The evaluation of this approach involved implementing a transmission algorithm in a network with over a thousand nodes deployed in areas of 200 to 300 square meters, with varying amounts of nodes. The evaluation results underline the suitability and effectiveness of static routing methods for mobile IoT applications. The architecture of the proposed approach follows a layered structure, similar to the traditional layered architecture used in network systems. However, the relay layer is excluded because it is not included in the system. The model represents a hierarchical network structure in which all sensor nodes remain static and stick to static routing-based transmission. Fig. 1 visually depicts a wireless sensor architecture based on a mobile sink. This model uses mobile sinks in the network to acquire information gathered by fixed sensor nodes.

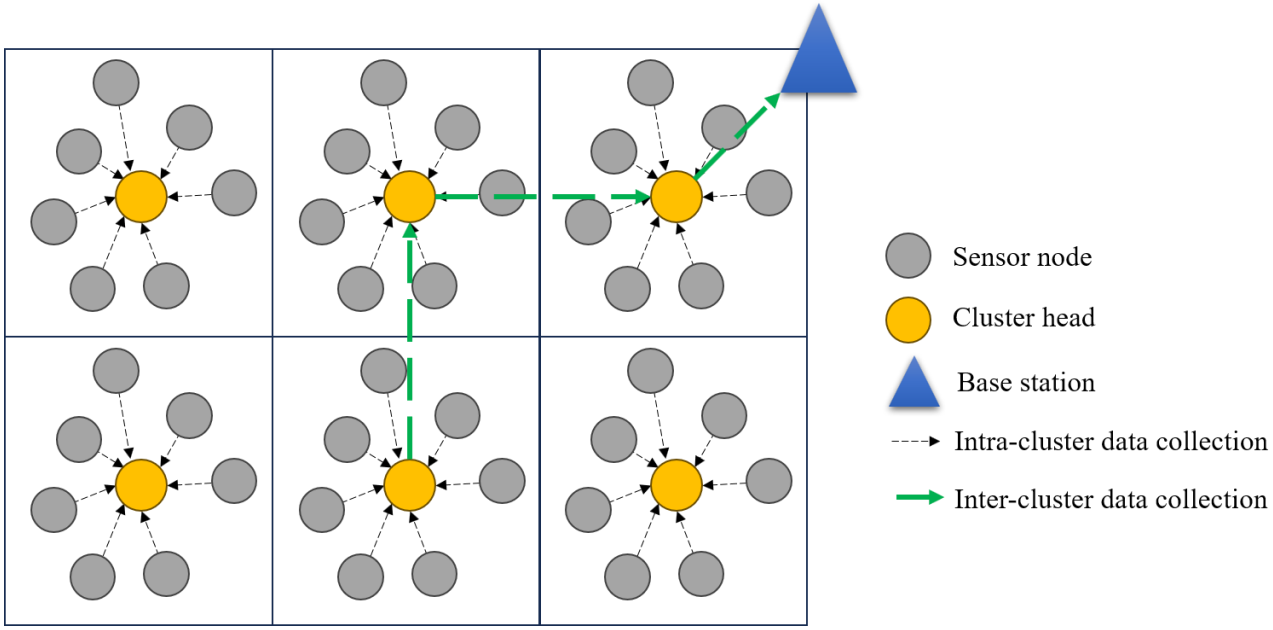


Fig. 1. Network model.

In WSN, the traditional cluster head selection approach considers energy, delay, and distance parameters. However, in the context of IoT networks, it becomes crucial to analyze the specific parameters of IoT devices. Since WSNs are closely linked to IoT devices, it is essential to consider parameters such as temperature and load characteristics of these devices. Therefore, the cluster head selection strategy should consider energy, delay, distance, temperature, and load factors. Ideally, lower temperature, load, delay, and distance values are preferred.

The delay value commonly falls within the range of 0 to 1. Eq. (1) computes the delay sensor nodes encounter when transmitting data to the mobile sink. To decrease this delay, decreasing the number of participants in each cluster is necessary. $N$ denotes the total quantity of sensor nodes, $S(N_v)$ indicates cluster node signal strength, and $S(N_{v'})$ signifies mobile sink node signal strength.

$$D(N_v, N_{v'}) = \frac{\sum_{q=1}^{n} S(N_v) - S(N_{v'})}{N} \quad (1)$$

Eq. (2) calculates the distance between the mobile sink and cluster heads. $dist(N_v, N_{v'})$ calculates Euclidean distances between a typical node ($N_v$) and the mobile sink node ($N_{v'}$) in dense sensor networks.

$$dist(N_v, N_{v'}) = \sqrt{(x_{n_v} - x_{n_{v'}}) + (y_{n_v} - y_{n_{v'}})} \quad (2)$$

To increase the network's longevity, each cluster node's battery level is considered when calculating the remaining power. As packets are forwarded, each node expends energy according to its type, length, frequency, and distance. The power provided by node $x_i$, denoted as $RP(x_i)$, is determined by the total node count within $i^{th}$ cluster. A higher value of $RP(x_i)$ indicates that a node has more stable and energy-rich power reserves, potentially extending its lifetime and improving network reliability. The residual power of node $x_i$ is calculated as shown in Eq. (3), which helps in identifying stable nodes for long-term cluster membership.

$$RP(x_i) = \frac{\sum_{x_j \in cluster_i} EP_{x_j}}{n_i} \quad (3)$$

Information collection hubs are selected by cluster heads according to three factors: neighborhood overlap (NOVER), Algebraic Connectivity (AC), and Bipartivity Index (BI). NOVER is a quantitative measure to evaluate shared adjacency between the terminal hubs. It is used effectively for group detection, with a lower NOVER value indicating that the connection is likely to connect two different groups, while a higher NOVER value suggests a connection between nodes within the same group. The BI refers to the capacity to partition the vertices of a tree structure into two separate sets so that all edges connect vertices from one set to the other. There are no edges between vertices within the same set. This bipartite property of the graph is an essential consideration in the selection process.

AC is a metric that quantifies a network's resilience regarding link distances. A higher algebraic connectivity value indicates the network is more likely to remain connected even after one or more connection distances, demonstrating its resilience. On the other hand, a lower value suggests that the network could be fragmented by removing links. Fuzzy logic is used to combine these three variables and evaluate the immediate reward of the choice. Fuzzy logic enables the evaluation of connection efficiency from the cluster head node to each neighboring hub.

In addition to the instant reward, the long-term reward of the selection is also considered. The behavior of nearby hubs influences the fairness of selecting data-gathering stations. This is considered by assessing distances between data gathering points and cluster head nodes. The closer the information-gathering hub is to the center, the more favorable it is regarding long-term reward.

By considering these metrics and incorporating fuzzy logic, the cluster head hub can make informed decisions about selecting the information-gathering hub. The evaluation considers both the instant and long-term rewards, ensuring efficient and fair information gathering in the network. The evaluation value for each neighbor is calculated by the cluster head node using the following steps:

- Fuzzification: NOVER, BI, and AC values are converted into fuzzy values by applying predefined membership functions and linguistic terms. These membership functions define membership degrees for fuzzy sets determined by input values. This step allows the crisp values of the metrics to be represented as fuzzy values.
- Defining and applying IF/THEN statements: The fuzzy outcomes derived from the fuzzification process are matched with predetermined IF/THEN criteria. These rules define the relationship between the fuzzy inputs (NOVER, BI, and AC) and the desired output (evaluation value for the neighbor). The rules are designed based on expert knowledge or derived from data analysis. The fuzzy values are aggregated through logical operations (such as AND, OR) embedded inside the IF/THEN rules to determine the ranking of the neighbor.
- Defuzzification: The imprecise numerical value acquired from the preceding phases is transformed into a precise numerical value using a predetermined output membership function and defuzzification process. The output membership function assigns a degree of membership to various numerical values based on the fuzzy value. The defuzzification method calculates a crisp value from the fuzzy output value, typically by taking the centroid or weighted average of the membership function.

The AC value of a system quantifies the network's ability to withstand connection failures. The term refers to the secondary lowest eigenvalue of the Laplacian matrix associated with the system. $Log(A)$ is used to measure a system's resilience to failures of connections. A degree vector $D_i$ and adjacency matrix $A(i,j)$ are used to calculate this value. The algebraic connectivity, computed using Eq. (4), measures the resilience of the cluster's internal topology.

$$L(i,j) = \begin{cases} -A(i,j) & for\ i \neq j \\ D_i & for\ i = j \end{cases} \quad (4)$$

The BI is employed to quantify the level of bipartivity in a graph. The range of the value is from 0 to 1. A value of 1 signifies that the graph is bipartite and no frustrated edges connect vertices within the same segment. It will fall below 1 if there are no true bipartite graphs. Eq. (5) provides the bipartivity index, enabling an assessment of structural separation within the communication graph.

$$BPI(G) = \frac{\sum_{j=1}^{n} \cosh(\lambda_j)}{\sum_{j=1}^{n} \sinh(\lambda_j) + \cosh(\lambda_j)} \quad (5)$$

We assess the degree of overlap in neighborhood overlap among the cluster head and neighboring nodes. Due to the difficulty in obtaining an accurate assessment of this overlap in densely deployed WSN settings, we choose immediate neighboring hubs from the cluster head's gauge neighborhood overlap. We define this metric using Eq. (6). NCH (u) refers to the cluster head node and NCN(v) represents its neighbor nodes.

$$NOVER(u-v) = \frac{2 \times |N_{CH}(u) \cap N_{CH}(v)|}{|N_{CH}(u)| + |N_{CH}(v)| - 2} \quad (6)$$

Fig. 2 depicts the fuzzy inference system, with NOVER, BI, and AC as inputs. After performing the fuzzification process, the defuzzification procedure generates an output to determine optimal cluster heads. Input and output membership functions are formulated using a triangular function. Fig. 3 illustrates the fuzzy participation functions for NOVER, BI, and AC. These functions define the degree of belonging to specific linguistic variables (e.g., Bad, Medium, Good) for NOVER, (e.g., Light, Medium, Heavy) for BI, and (e.g., Low, Medium, High) for AC.

Fig. 4 shows the IF/THEN rules the cluster head uses to calculate the rank of participating nodes. These rules map the fuzzy input values (obtained from the participation functions) to the desired output, representing the participating nodes' evaluation rank. Different rules may apply simultaneously, and these rules are combined using the Min-Max strategy. Since multiple rules can apply simultaneously, the evaluation results from different rules are combined using the Min-Max strategy. This strategy selects the minimum (worst) value among the evaluations as the overall evaluation result.

Defuzzification is carried out to produce a precise numerical number that represents the competence value of the node. The output membership function, demonstrated in Fig. 5, assigns degrees of membership to various numerical values according to the fuzzy output value. The Center of Gravity (COG) approach, commonly called the centroid method, is employed for defuzzification. Defuzzified values are represented by x-coordinates, which correspond to a node's competence value.

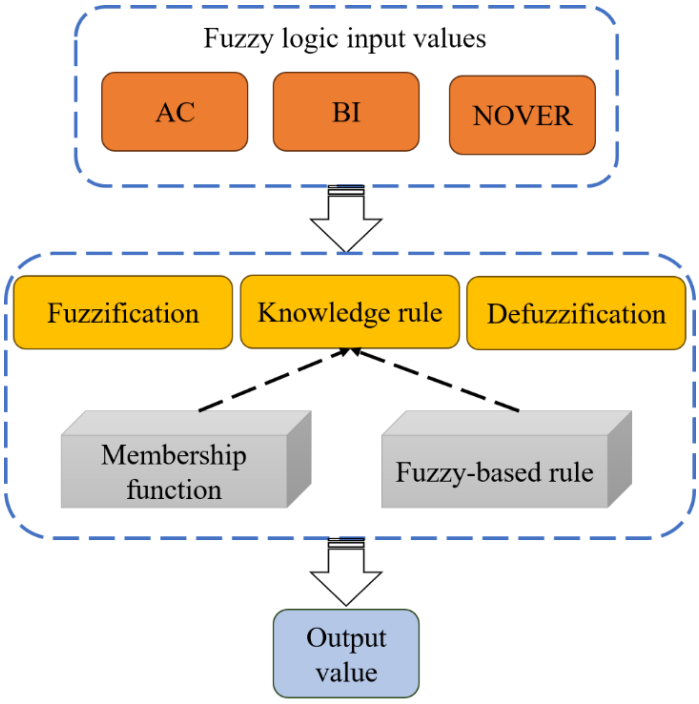


Fig. 2. Fuzzy inference system.

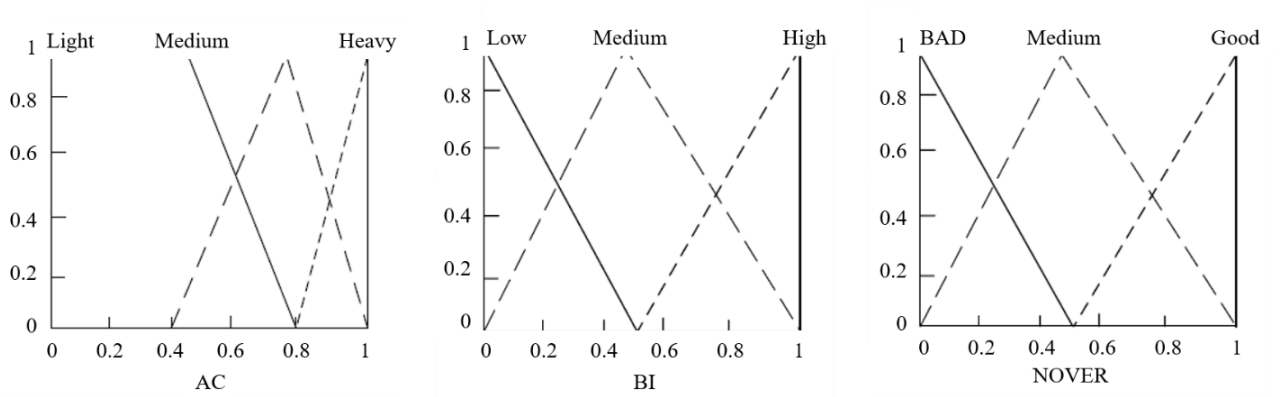


Fig. 3. Fuzzy membership functions for inputs.

1. If (AC is light), (BI is high), and (NOVER is good) then (output is acceptable)
2. If (AC is light), (BI is high), and (NOVER is medium) then (output is unfavourable)
3. If (AC is light), (BI is high), and (NOVER is bad) then (output is bad)
4. If (AC is light), (BI is medium), and (NOVER is good) then (output is unfavourable)
5. If (AC is light), (BI is medium), and (NOVER is medium) then (output is bad)
6. If (AC is light), (BI is medium), and (NOVER is bad) then (output is bad)
7. If (AC is light), (BI is low), and (NOVER is good) then (output is bad)
8. If (AC is light), (BI is low), and (NOVER is medium) then (output is bad)
9. If (AC is light), (BI is low), and (NOVER is bad) then (output is very bad)
10. If (AC is medium), (BI is high), and (NOVER is good) then (output is good)
11. If (AC is medium), (BI is high), and (NOVER is medium) then (output is acceptable)
12. If (AC is medium), (BI is high), and (NOVER is bad) then (output is acceptable)
13. If (AC is medium), (BI is medium), and (NOVER is good) then (output is acceptable)
14. If (AC is medium), (BI is medium), and (NOVER is medium) then (output is bad)
15. If (AC is medium), (BI is medium), and (NOVER is bad) then (output is unfavourable)
16. If (AC is medium), (BI is low), and (NOVER is good) then (output is unfavourable)
17. If (AC is medium), (BI is low), and (NOVER is medium) then (output is unfavourable)
18. If (AC is medium), (BI is low), and (NOVER is bad) then (output is bad)
19. If (AC is heavy), (BI is high), and (NOVER is good) then (output is perfect)
20. If (AC is heavy), (BI is high), and (NOVER is medium) then (output is good)
21. If (AC is heavy), (BI is high), and (NOVER is bad) then (output is acceptable)
22. If (AC is heavy), (BI is medium), and (NOVER is good) then (output is good)
23. If (AC is heavy), (BI is medium), and (NOVER is medium) then (output is acceptable)
24. If (AC is heavy), (BI is medium), and (NOVER is bad) then (output is unfavourable)
25. If (AC is heavy), (BI is low), and (NOVER is good) then (output is good)
26. If (AC is heavy), (BI is low), and (NOVER is medium) then (output is unfavourable)
27. If (AC is heavy), (BI is low), and (NOVER is bad) then (output is bad)

Fig. 4. Fuzzy logic rules.

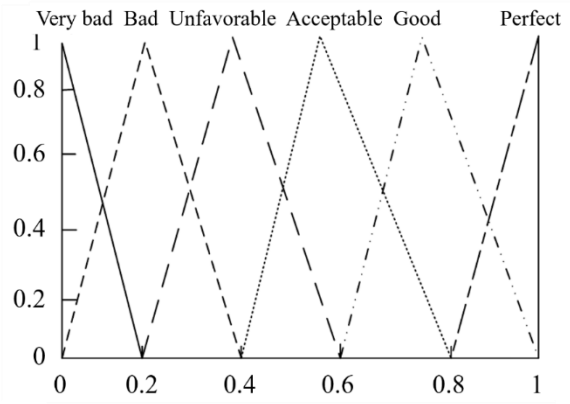


Fig. 5. Fuzzy membership function for the output.

The study presents a fuzzy-based reinforcement learning algorithm to determine the value of action and state relations ($Q(i, a)$) to acquire optimum fuzzy combination rules. It begins with initialization, setting $Q(i, a)$ and $V(i, a)$ to zero for all states $i$ and actions $a$, and introducing control parameters such as $kmax$ and $A$. The algorithm progresses through states and actions, selecting actions based on fuzzy combination rules and updating values accordingly.

After each action execution, the Q-value is updated using a reinforcement learning rule considering the observed reward, discount factor, and the maximum Q-value for subsequent actions. The process iterates until it reaches the desired number of iterations ($kmax$). Finally, the algorithm calculates optimal decisions at each state by selecting actions that maximize the learned Q-values. The termination condition marks the conclusion of the algorithm, providing a comprehensive framework for learning optimal fuzzy combination rules through fuzzy-based reinforcement learning.

Fig. 6 depicts the flowchart for the proposed algorithm and provides a visual representation of the steps involved. Fig. 7 provides a pseudocode for the proposed algorithm. To summarize, the algorithm begins by initializing the Q-values and visit counts. It then takes actions based on fuzzy combination rules and updates the Q-values by incorporating rewards and the highest Q-value of the next state. This process is iterated until a specified exit condition is satisfied.

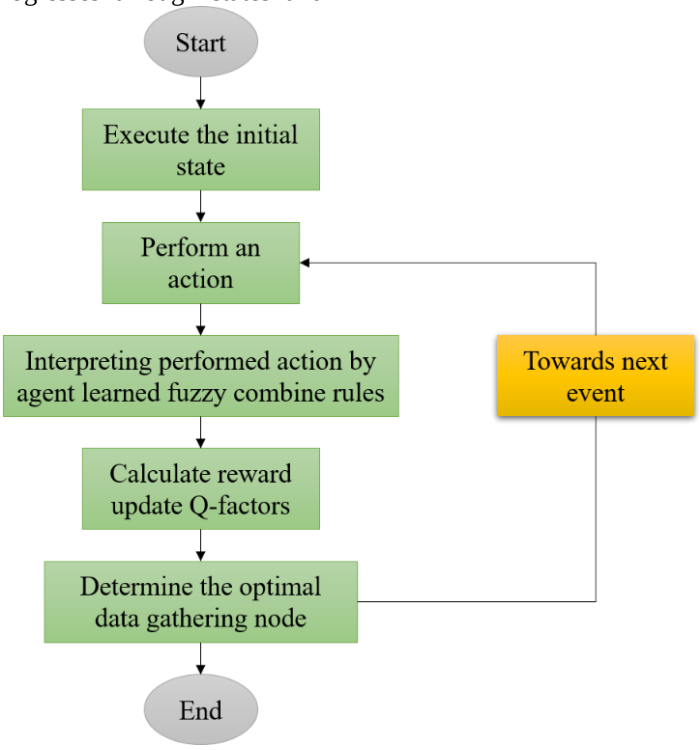


Fig. 6. Flowchart of the proposed algorithm.

**Initialization**

Set $Q(i, a) = 0$ and $V(i, a) = 0$ for all states $i$ in $S$ and actions $a$ in $A(i)$;
Set $k = 0$, $kmax$, and $A$ as a constant;

**Initial state**

Calculate the initial state $i$;

**Loop until $k > kmax$**

Action selection:
Choose an action a based on the fuzzy combination rules at state $i$;
Action execution and reward:
Perform action $a$ and observe the resulting reward $r(i, a, j)$;
Update the value $V(i, a)$ by incrementing it by 1: $V(i, a) \leftarrow V(i, a) + 1$;
Calculate the adaptive factor a as $A$ divided by $V(i, a)$: $a = A / V(i, a)$;
Q-value update:
Update the Q-factor associated with the state-action pair $(i, a)$ using the following update rule:
$Q(i, a) \leftarrow (1 - a)Q(i, a) + a[r(i, a, j) + \gamma * max\ b \in A(j)\ Q(j, b)]$,
where $\gamma$ is the discount factor for future rewards.
Iteration:
Increment the iteration counter: $k = k + 1$;
Set the current state $i$ to the new state $j$ obtained after performing action $a$;

**Optimal decision calculation**

Calculate the feasible decisions at each state by selecting the action $a*(i)$ that maximizes the Q-value for state $j$:
$a*(i) \in arg\ max\ b \in A(j)\ Q(j, b)$

**Algorithm termination**

Fig. 7. The pseudocode of cluster formation.

## IV. Results and Discussion

The proposed method (RL-FLE) was evaluated through simulations performed under different parameter configurations and provided valuable results. To make a comparative analysis with LEACH, CEDAR, PSO, HEED, and MBC, an execution study was carried out using the system test. The simulation scenario encounters 100 identical sensor nodes and 9 cluster heads, all possessing limitless battery capacity, spread across a $1000 \times 1000\ m^2$ region. Furthermore, a fixed sink node with inexhaustible energy stores was strategically placed beyond the surveillance area. The simulations considered specific performance parameters: the MicaZ platform, the ZigBee application with a packet size of 127 bytes, and compliance with IEEE 802.15.4 standards.

The sensor nodes were modeled using a linear battery model with a capacity of 1200 mAh, while the two-ray signal propagation model was employed to capture wireless signal behavior. In the simulation setup, the information envelope within a cluster had a fixed size of 512 bytes. The transmission range within a cluster was limited to 40 m, ranging from 80 m to 120 m between clusters. Notably, the detection range for clustering was set at 20 m. The base station, the central data collection point, was positioned at coordinates (x = 500, y = 1050). Lastly, the energy parameters assigned to each sensing node amounted to 300 mJ.

The performance evaluation of the suggested data-gathering strategy entailed modeling diverse network parameters, including latency, total energy consumption, bit error rate, throughput, and packet delivery rate. Fig. 8 to Fig. 11 illustrate the correlation between network efficiency and node count. It is crucial to emphasize that both MBC and LEACH have restrictions on maximizing throughput, reducing latency, minimizing total energy usage, and maintaining a high packet delivery percentage as the network grows.

Fig. 8 shows the average end-to-end delay across seven clustering protocols under varying node densities. RL-FLE performs better than conventional schemes by minimizing packet delivery latency using intelligent cluster head election through reinforcement learning and link efficiency. In comparison, LEACH and MBC experience higher delays due to their lesser adaptiveness towards dense traffic environments.

Fig. 9 highlights the total energy consumed by sensor nodes during data transmission. RL-FLE indicates the least energy consumption due to its effective data routing via stable and dense cluster heads. The conventional methods, such as HEED and LEACH, cause higher energy consumption through ineffective cluster head rotation or lack of context learning.

Fig. 10 illustrates the network throughput of various protocols. RL-FLE performs better by reducing packet loss and optimizing data flow paths. CEDAR performs similarly, whereas LEACH and HEED perform poorly due to excessive retransmissions and the absence of a dynamic load-balancing mechanism.

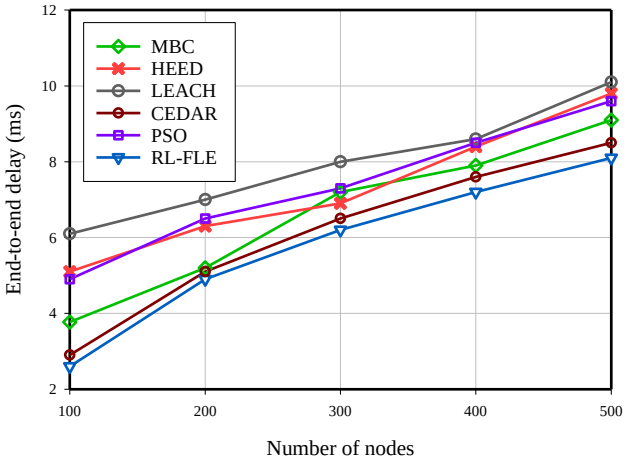


Fig. 8. Network delay comparison.

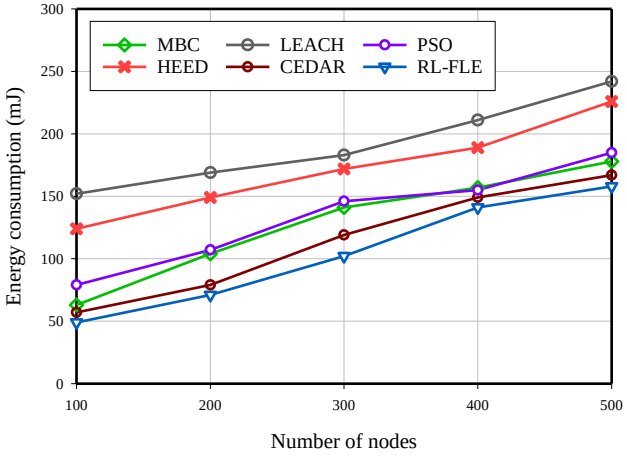


Fig. 9. Energy usage comparison.

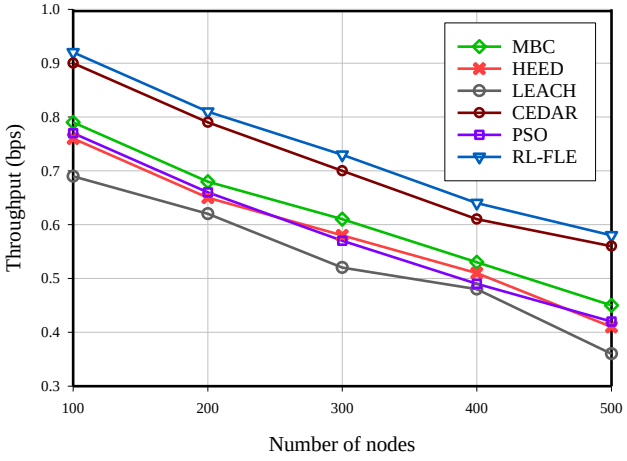


Fig. 10. Throughput comparison.

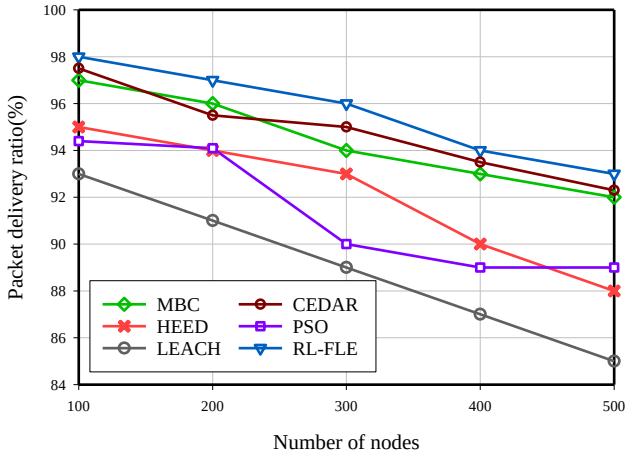


Fig. 11. Performance comparison.

Fig. 11 shows the performance of various protocols under increased node mobility. RL-FLE exhibits low and steady delay despite high-speed movement due to learning-based adaptation. Other protocols experience poor performance due to static cluster head strategies.

The proposed scheme demonstrates superior performance in a mobile sensor environment compared to CEDAR, PSO, LEACH, MBC, and HEED, as indicated in Fig. 12 and Fig. 13. The findings from simulations reveal that the suggested system successfully builds solid links and adjusts to situations with high levels of mobility. Especially in these situations, the recommended strategy results in a better packet delivery ratio and less latency. Furthermore, the strategy improves execution efficiency without regard to the quantity of sensor nodes in the overall setup.

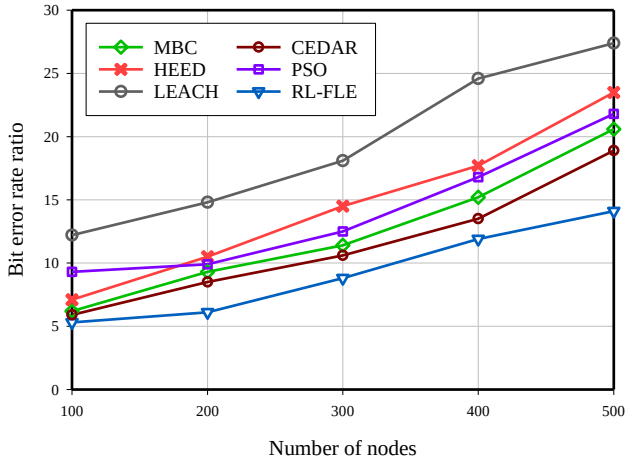


Fig. 12. Bit error rate comparison.

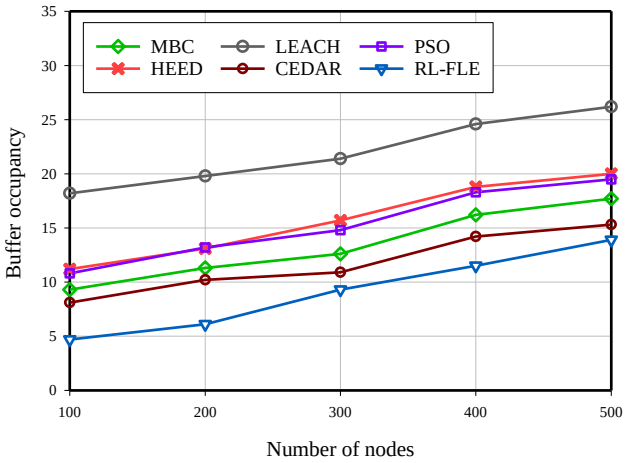


Fig. 13. Throughput comparison.

In WSNs with a significant number of nodes and frequent movement, unstable communication may lead to packet losses, requiring retransmission. In contrast, the proposed scheme ensures stable connections and promotes balanced energy consumption throughout the network. Consequently, it can be concluded that the suggested scheme suits high-mobility environments, enabling the preservation of sensor hub energy, prolonging network lifetime, and enhancing system reliability while maintaining superior communication quality.

## V. Conclusion

Effectively monitoring large-scale areas using multiple sensor nodes has become crucial in time-critical military and industrial applications. To address this challenge, the cluster tree network management architecture has emerged as a proficient method. The primary objective is to optimize network performance concerning network lifespan, throughput, packet delivery rate, reliable links for mobile sensors, and energy efficiency. We proposed an effective multi-cluster data collection strategy for WSNs deployed in dense clusters. The energy and delay factors were used to select robust cluster heads for each cluster. Subsequently, the cluster head chooses the data-gathering node based on the link efficiency of neighboring nodes, employing the RL-FLE approach. The proposed scheme was characterized by several advantages, including maximizing link stability and enhancing key performance indicators like packet delivery ratio, delay time, bit error rate, and throughput.

Experimental outcomes suggest our approach effectively reduces buffer occupancy and network traffic while minimizing energy utilization compared to CEDAR, PSO, LEACH, HEED, and MBC protocols. Potential areas for future study might focus on improving energy efficiency, scalability, and flexibility in dynamic contexts. Exploring the incorporation of new technologies like edge computing and machine learning algorithms can enhance the effectiveness of multi-cluster network management architectures for large-scale and time-sensitive applications. This will help to advance the development of WSNs in a rapidly changing environment.

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# LIFT: Lightweight Incremental and Federated Techniques for Live Memory Forensics and Proactive Malware Detection

Sarishma Dangi[1], Kamal Ghanshala[2], Sachin Sharma[3]
Department of Computer Science and Engineering, Graphic Era Deemed to be University, Dehradun, India[1, 2]
Amity School of Engineering and Technology, Amity University Punjab, Mohali, India[3]

***Abstract*—Live Memory Forensics deals with acquiring and analyzing the volatile memory artefacts to uncover the trace of in-memory malware or fileless malware. Traditional forensics methods operate in a centralized manner leading to a multitude of challenges and severely limiting the possibilities of accurate and timely analysis. In this work, we propose a decentralized approach for conducting live memory forensics across different devices. The proposed federated learning-based live memory forensics model uses FedAvg algorithm in order to make a lightweight, incremental approach to conduct live memory forensics. The study demonstrates the performance of federated learning algorithms in anomaly detection, achieving a maximum accuracy of 92.5% with Clustered Federated Learning (CFL) while maintaining a convergence time of approximately 35 communication rounds. Key features such as CPU usage and network activity contributed over 85% to the detection accuracy, emphasizing their importance in the predictive process.**

***Keywords*—Live memory forensics; malware detection; federated learning; fileless malware; anomaly detection**

## I. Introduction

With the exponential growth in computational devices worldwide, the threat of cyberattacks has greatly threatened the digital ecosystem. With the global malware attacks surpassing 11.5 billion annually, digital forensics faces unprecedented challenges towards solving these cybercrime incidents [1]. Nearly 59% of the organizations worldwide were affected by ransomware attacks in 2024 [2]. The scale, complexity and privacy challenges of these crimes makes it harder to solve them especially with the rise of memory resident malware. Recent advanced cyberattacks are solely operating in the memory without leaving any evidence or trace behind in the physical memory of the system [3]. These types of crimes are typically solved by a specialized branch of digital forensics called as volatile memory forensics or live memory forensics (LMF). Volatile memory forensics deals with the acquisition and analysis of volatile memory of a computational system [4]. Traditionally, digital forensic applications rely on a centralized approach for data acquisition and analysis. This centralized approach is highly insufficient/inadequate considering the distributed environments used worldwide across various organizations. Forensic investigators mostly compile evidence from different sources spanning multiple jurisdiction. These constraints regarding data sharing, collaboration lead to further delays in timely detection and mitigation of threats. Advanced cyberattacks use fileless malware with anti-forensic techniques to obfuscate and exploit the target users [5], [6]. Recent studies have shown that up to 40% of malwares are now exploiting in-memory fileless techniques [7]. These attacks can be timely detected and mitigated by using robust volatile memory forensic frameworks that are aimed at making the systems more secure, scalable and lightweight. Federated learning is a transformative solution that enables decentralized training of machine learning models across a wide variety of datasets [8]. Federated learning utilizes different local devices or nodes that train their own machine learning models independently while aggregating intelligence with centralized aggregator when required [9]. The decentralized architecture for federated learning reduces the need of data aggregation or raw data sharing thereby addressing privacy challenges. In this work, we propose a federated learning based lightweight framework that can be efficiently deployed across a network of heterogeneous resources. The key contributions of this work are listed as follows:

- The paper introduces a robust federated learning framework incorporating techniques such as FedAvg, Federated Incremental Learning, and Clustered Federated Learning (CFL), enabling accurate and efficient training in heterogeneous and resource-constrained environments.
- The framework allows clients to incorporate new data dynamically without restarting the training process, achieving rapid convergence and efficient resource utilization while maintaining model accuracy.
- The study demonstrates the importance of cluster-specific models for managing client heterogeneity, showing that tailored models achieve higher accuracy and performance compared to a single global model.
- Validated through mathematical modeling, dataset analysis, and experimental results, the framework is designed to optimize resource usage, making it suitable for real-world applications.

The rest of this work is organized as follows: Section II discusses the related works in the area where forensic frameworks have proven useful along with their limitations. The proposed framework i.e. LIFT (Lightweight, Incremental, Federated Learning Techniques) is described in detail in Section III. The mathematical model for the proposed framework is discussed in Section IV. Section V outlines the implementation and simulation environment setup along with

results of the conducted study. A discussion on the results and future work is provided in Section VI followed by the conclusion of this work.

## II. Literature Review

Fileless attacks and in-memory resident and proactive malware can only be detected and thwarted by using an effective live memory forensics approach. Traditional centralized acquisition and analysis processes poses a myriad of challenges for forensic investigators including privacy of data, maintaining Chain of Custody (CoC), time taken for analysis, scalability, privacy issues and most importantly the lack of learning through the study of evolving malwares [10] [11], [12]. Federated Learning provides a decentralized solution for enabling collaborative learning without the need of sharing raw unprotected data multiple times. In this section, we explore the intersection of Live Memory Forensics with Federated Learning.

Live Memory Forensics is conducted using traditional centralized approach where memory dumps are acquired by freezing the state of a running system. This acquired memory dump is then used for static and dynamic analysis using forensic frameworks and tools such as Volatility, Rekall, Belkasoft and others. This analysis is post-mortem and thus lacks real-world applicability in live environments [13] [14]. Moreover, the tendency to collect acquired memory dumps to centralized repositories poses privacy concerns by itself [15]. Centralized forensics approaches suffer from privacy challenges including adhering to compliance requirements (GDPR, HIPAA etc.), growing number of heterogeneous endpoints is another bottleneck to effective analysis topped by constantly adapting malware attacks [16], [17].

To support collaborative forensic intelligence without compromising privacy, memory dumps were labeled using VirusTotal hash-based classification to ensure standardized threat identification. Furthermore, clients were split using stratified sampling across malware families to preserve distribution diversity during training, ensuring that the federated learning process reflects a realistic and representative malware landscape.

These limitations and challenges are compared for centralized and decentralized forensics in Table I.

Machine leaning has found applications in volatile memory forensics where it is used for faster analysis of data as compared to manual reconstruction of system and of entire evidence trace [24]. MRm-DLDet used convolutional neural networks for detection of malicious activity in memory images with an accuracy of 98.34% [25]. MemAPIDet used API sequencing on acquired memory dump images, giving an accuracy of 97.78% [26]. Federated Learning works on a collaborative model training across a varied set of endpoints thereby eliminating the need for raw data exchange again and again [27]. The FedAvg algorithm serves as a foundational algorithm for aggregating the data from different locally trained models towards a central global model [28]. Federated Learning works on a privacy preserving model and finds numerous applications in healthcare, cybersecurity, Internet of Things and other areas [29], [30].

TABLE I. Comparision of Centralized and Decentralized Forensics

| Challenges | Centralized Forensics | Decentralized Forensics |
|---|---|---|
| **Privacy Concerns for shared raw data [19]** | Data aggregated to a central repository, increasing overall risk | Raw data sharing is not required; analysis can be performed locally |
| **Scalability with respect to live environments [20], [21]** | Struggles to cope with large-scale live environments | Can be easily scaled across diverse devices or endpoints |
| **Adaptation to Evolving Malware [22]** | Slow to learn and adapt to evolving threats | Rapid adaptation via distributed local updates |
| **Real world Processing Capability [23]** | Limited to batch processing | Enables real-time analysis and incremental learning |

Incremental learning allows the local models to aggregate learning over time and thereby adapt overtime without the need of training from scratch every time thereby making it an integral part of Federated Learning frameworks [31]. Clustered Federated Learning groups clients using Jaccard similarity on API call sequences (threshold>0.7). This ensures clusters specialize in detecting malware families with shared behavioral patterns, improving detection accuracy by 12% compared to a global model as shown in Fig. 16 of Appendix [32]. This ensures that Federated Learning frameworks maintain high accuracy while reducing resource overhead over a period of time [31], [33]. Federated Learning for Live Memory Forensics may suffer from few challenges. Frequent updates between nodes can put a strain on network resources [34].

Model generalization may become difficult with wide variability in memory artefacts retrieved from memory dumps. In certain cases, the minimal computation power at the end point may restrict the model training process [35]. Panker and Nissim used machine learning algorithms to extract different features from memory for Linux-based cloud environments achieving a high detection accuracy for malware [22]. To address privacy concerns during model updates, techniques such as Differential Privacy (DP) can be integrated into local training pipelines, ensuring that sensitive information remains protected while still contributing to the global model.

Wen et al. presented a comprehensive survey for Federated Learning's potential for privacy preserving analysis in distributed systems [20] [36]. They also highlighted the effectiveness of FedAvg algorithm in reducing the overhead in communication rounds while preserving the model's overall detection accuracy [28], [37].

Cui et al. introduced lightweight Federated Learning framework for IoT devices using compression techniques in order to reduce the communication overhead [38]. Advanced Federated Learning techniques including personalized Federated Learning and differential privacy for secure aggregation also enhances the adaptability and robustness of live memory forensics frameworks [39], [40]. Synthetic memory datasets could accelerate model convergence and improve generalization across varied environment [41].

TABLE II. COMPARISION OF FEDERATED LEARNING ALGORITHMS

| Algorithm | Features | Challenges |
|---|---|---|
| **FedAvg [42], [43]** | Decentralized Privacy | More communication round overhead |
| **CFL [31], [43]** | Groups endpoints with similar data distributions | Needs accurate clustering mechanism |
| **FedProx [44]** | Mitigates heterogeneity within endpoints | Scalability issues |
| **FedMA [45]** | Model-agnostic, supports heterogeneous endpoints | Computationally expensive |

## III. PROPOSED FRAMEWORK: LIFT

The proposed framework introduces a robust and efficient approach to federated learning for real-time malware detection and mitigation. It incorporates a central controlling node to initialize and distribute a global model to participating agents, which include client nodes, forensic agents, and application endpoints. Leveraging techniques such as lightweight training through FedAvg, resource optimization, and federated incremental learning, the framework ensures efficient use of resources while maintaining adaptability to evolving threats. Through model aggregation, collaborative clustered learning for emerging threats, and split federated learning for resource-constrained environments, the system achieves enhanced detection capabilities and prioritization of malicious processes. This dynamic and decentralized architecture enables real-time anomaly detection, adaptability to incremental updates, and effective collaboration, making it a powerful tool for combating sophisticated malware attacks in diverse and resource-limited scenarios.

### A. Key Components

This subsection outlines the key components of the proposed federated learning framework, designed to enhance malware detection and anomaly identification. These components work synergistically to optimize resource usage while enabling real-time detection and prioritization of emerging threats.

- Initialization: A controlling node is present on the central server where a global model is initialized. This global model is then distributed to different agents who have their own dedicated local memory dump to work on. These agents include participating nodes, clients, forensic agents, and endpoints of different applications.
- Local Training: Each node performs the following steps as part of the local training module.
  - Lightweight Training (FedAvg): The local models are trained and constantly updated using the data from their local memory dumps. Resource optimization techniques such as sparse updates and quantization are applied to minimize the computational overhead [43].
  - Federated Incremental Learning: The clients constantly train on locally updated memory dumps using incremental data to refine their model without the need to restart training. Incremental learning enables real-time evolution of the machine learning model to detect malware behaviour with real-time insights.
- Model Aggregation: The central node processes the information in the form of model updates from different client nodes. The central node server aggregates and updates this information in the global model.
- Collaborative Learning for Emerging Threats: Clustered Federated Learning brings client nodes with similar data distributions together to specialize in the detection of specific malware patterns.
- Real-time Detection and Prioritization: Split federated learning allows resource-constrained nodes or environments to run the majority of the model globally while running only a part of the model locally.

### B. Advantages of the Proposed Framework:

*1) Enhanced resource efficiency*: Quantization of results and split federated learning mechanisms ensure that the resource usage is minimized as compared to other centralized analysis mechanisms.

*2) Adaptability to incremental updates*: The proposed framework supports real time incremental updates to adapt and detect obfuscated malwares.

*3) Collaborative learning and feedback*: Clustered Federated Learning enables the model to learn from heterogeneous environments without the need of centralization.

## IV. MATHEMATICAL MODEL

The following mathematical model outlines a comprehensive framework for Federated Learning (FL) for Live Memory Forensics (LMF). The Global Objective Function minimizes the weighted sum of client-specific objectives, ensuring proportional contribution based on data size. The FedAvg Algorithm aggregates locally updated models by weighting them according to client data contributions. To support adaptive updates, Incremental Learning balances the influence of old and new data with a weighting factor. Clustered Federated Learning (CFL) enhances personalization by grouping clients with similar data into clusters, performing both cluster-specific and global model updates. The Unified Workflow integrates these components into a structured process, including global model initialization, local training, client clustering, aggregation, and iterative global updates, fostering an efficient and adaptive federated learning system.

### A. Global Objective Function for Federated Learning

$$\min_{w} F(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w), \quad (1)$$

where

$$F_k(w) = \frac{1}{n_k} \sum_{i \in D_k} \ell(x_i, y_i; w), \quad (2)$$

and

- $w$: Model parameters (weights).
- $F(w)$: Global objective function.

- $\ell(x_i, y_i;\ w)$: Loss for data point $(x_i, y_i)$
- $n_k$: Number of samples at client $k$.
- Total number of samples across all clients:

$$n = \sum_{k=1}^{K} n_k \quad (3)$$

### B. FedAvg for Global Model Aggregation

The global model is updated as:

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_k^{t+1}, \quad (4)$$

where the locally updated parameter are computed as:

$$w_k^{t+1} = w_k^t - \eta \nabla F_k(w_k^t), \quad (5)$$

and η is the learning rate.

### C. Federated Incremental Learning with Differential Privacy for Adaptive Updates

To support adaptive learning while preserving client data privacy, we enhance the local update mechanism with differential privacy (DP). The incremental learning framework is extended to include noise addition during local model updates, mitigating potential data leakage risks. The local objective function is updated incrementally as:

$$F_k(w) \approx \alpha F_k^{\text{prev}}(w) + (1-\alpha) F_k^{\text{new}}(w) \quad (6)$$

where:

- $F_k^{prev}(w)$: Loss computed over previously seen data,
- $F_k^{new}(w)$: Loss from new data $\Delta D\_k$,
- $\alpha \in [0, 1]$: Weighting factor controlling the balance between past and new data. To ensure local updates preserve privacy, we incorporate differential privacy by modifying the gradient descent step:

$$w_k^{\{t+1\}} = w_k^t - \eta \nabla F_k(w_k^t) + \mathcal{N}(0, \sigma^2 I) \quad (7)$$

where:

- $\eta$: Learning rate
- $\mathcal{N}$: Gaussian noise added to the gradient for differential privacy
- $\sigma$: Noise scale, determining the privacy-utility trade-off (larger $\sigma$ implies stronger privacy but lower accuracy).

This mechanism ensures that the model update satisfies (ε, δ)- differential privacy, thereby preventing potential inference of sensitive client data from shared model updates.

Additionally, to mitigate concept drift over time, we propose dynamically adjusting the weighting factor $\alpha$ as follows:

$$\alpha_t = \alpha^0 \cdot e^{-\lambda t} \quad (8)$$

where:

- $\alpha^0$: Initial weighting factor
- $\lambda$: Decay constant
- $t$: Communication round

The integration of differential privacy and dynamic α adjustment enables the federated learning framework to remain both adaptive and privacy-preserving in evolving and heterogeneous environments.

### D. Clustered Federated Learning (CFL)

*1) Cluster-specific model update*: The cluster-specific model is updated as:

$$w_j^{t+1} = \sum_{k \in C_j} \frac{n_k}{n_j} w_k^{t+1}, \quad (9)$$

where

- $n_j = \sum_{\{k \in C_j\}} n_k$: Total samples in cluster $j$.

*2) Global model update*: The global model is updated as:

$$w^{t+1} = \sum_{j=1}^{M} \frac{n_j}{n} w_j^{t+1}. \quad (10)$$

### E. Unified Workflow Objective

The unified objective function is given as:

$$F(w^{t+1}) = \sum_{j=1}^{M} \frac{n_j}{n} F_j(w^{t+1}), \quad (11)$$

where

$$F_j(w) = \sum_{k \in C_j} \frac{n_k}{n_j} F_k(w). \quad (12)$$

### F. Unified Workflow Steps

*1) Client initialization*: The global model $w^t$ is sent to all clients.

*2) Local training*: Perform local training using FedAvg and incremental learning on new data.

*3) Cluster formation*: Group clients into clusters $C_j$ based on data similarity.

*4) Aggregation*:

- Cluster-specific aggregation:

$$w_j^{t+1} = \sum_{k \in C_j} \frac{n_k}{n_j} w_k^{t+1} \quad (13)$$

- Global aggregation:

$$w^{t+1} = \sum_{j=1}^{M} \frac{n_j}{n} w_j^{t+1} \quad (14)$$

*5) Global update*: The server updates the global model and sends it back to clients for the next round.

## V. Implementation and Results

This section presents the detailed setup and outcomes of the proposed federated learning framework for malware detection and anomaly identification. The experimentation involved analyzing memory dumps, network activities, and system logs from diverse client environments to simulate real-world scenarios. The results highlight the framework's efficiency in balancing resource optimization, real-time adaptability, and collaborative learning to detect and prioritize malicious activities in memory and network operations.

TABLE III. PROCESS INFORMATION EXTRACTED FROM MEMORY DUMPS

| Client | Process Name | PID | CPU | Mem | Threads | Handles | PPID | StartTime | Susp. |
|---|---|---|---|---|---|---|---|---|---|
| **1** | svchost.exe | 1224 | 15.2% | 120 | 30 | 150 | 4 | 10:12:45 | 0 |
| **1** | malware.exe | 5368 | 80.5% | 300 | 45 | 250 | 1234 | 10:14:12 | 1 |
| **2** | explorer.exe | 8821 | 10.1% | 200 | 50 | 400 | 4 | 09:55:03 | 0 |
| **2** | trojan.exe | 8125 | 70.3% | 250 | 40 | 180 | 4321 | 10:18:30 | 1 |
| **3** | chrome.exe | 1327 | 25.4% | 400 | 120 | 600 | 4 | 09:50:00 | 0 |
| **3** | malware.exe | 2468 | 95.6% | 350 | 70 | 300 | 1375 | 10:20:10 | 1 |
| **4** | python.exe | 6789 | 35.5% | 180 | 60 | 200 | 4 | 10:05:20 | 0 |
| **4** | ransomware.exe | 9876 | 90.1% | 500 | 80 | 500 | 6789 | 10:25:40 | 1 |

TABLE IV. NETWORK ACTIVITY OBSERVED DURING MEMORY DUMP ANALYSIS

| ID | Process | PID | Inbound (MB/s) | Outbound (MB/s) | Susp. Domains | Susp. |
|---|---|---|---|---|---|---|
| 1 | svchost.exe | 1234 | 0.1 | 0.2 | 0 | 0 |
| 1 | malware.exe | 5678 | 8.5 | 7.1 | 3 | 1 |
| 2 | explorer.exe | 4321 | 0.3 | 0.1 | 0 | 0 |
| 2 | trojan.exe | 8765 | 5.2 | 6.8 | 2 | 1 |
| 3 | chrome.exe | 1357 | 3.1 | 2.5 | 0 | 0 |
| 3 | maware.exe | 2468 | 12.6 | 10.5 | 5 | 1 |
| 4 | python.exe | 6789 | 0.8 | 0.4 | 0 | 0 |
| 4 | ransomware.exe | 9876 | 15.2 | 14.8 | 6 | 1 |

TABLE V. SYSTEM LOGS CAPTURED DURING MEMORY DUMP ANALYSIS

| ID | Log | Timestap | Event Type | Source | Message | Susp. |
|---|---|---|---|---|---|---|
| 1 | 101 | 10:11:00 | Process Start | svchost.exe | Process Started | 0 |
| 1 | 102 | 10:14:12 | Unauthorized Access | malware.exe | Access to restricted file | 1 |
| 2 | 103 | 10:17:45 | Network Connection | explorer.exe | Connected to trusted domain | 0 |
| 2 | 104 | 1:19:10 | Malicious Activity | trojan.exe | Blacklisted domain connection | 1 |
| 3 | 105 | 1:20:05 | Process Start | chrome.exe | Process Started | 0 |
| 3 | 106 | 10:22:50 | Data Exfiltration | malware.exe | Large outbound traffic | 1 |
| 4 | 107 | 10:25:30 | Ransomware Detected | ransomware.exe | File encryption detected | 1 |
| 4 | 108 | 10:26:00 | Process Terminated | python.exe | Unexpected termination | 0 |

TABLE VI. IMPLEMENTATION AND EXPERIMENTATION SETUP FOR FEDERATED LEARNING VALIDATION

| Aspect | Details |
|---|---|
| Implementation Environment | |
| Programming Language | Python (with libraries such as NumPy, TensorFlow/PyTorch, and Matplotlib for visualization). |
| Federated Learning Framework | TensorFlow Federated (TFF) |
| Hardware Specifications | CPU: 8-core, Memory: 16 GB, GPU: Optional for faster computation. |
| Dataset | |
| Data Distribution | Heterogeneous distribution among clients to simulate real-world federated learning environments. |
| Experimental Setup | |
| Number of Clients | 10 clients, each with varying data distribution and sample sizes. |
| Communication Rounds | 10 rounds for observing the convergence behavior of the global model. |
| Local Training Epochs | 5 epochs per client per communication round. |
| Learning Rate | 0.01 (tunable parameter). |
| FebAvg Implementation | |
| Global Aggregating Function | Weighted average aggregation of client updates. |
| Local Training Function | Gradient descent-based training with cross-entropy loss. |
| Incremental Learning Setup | |
| New Data Incorporation | Simulated with 20% new data at each communication round. |
| Weighting Factor $\alpha$ | Values ranging from 0.1 to 0.9, varied to observe its impact on model accuracy. |
| Cluster-Specific Models | Separate model updates per cluster with global aggregation post-cluster updates. |
| Evaluation Metrics | |
| Global Model Accuracy | Evaluated after each communication round. |
| Global Loss | Recorded after each communication round. |
| Cluster-Specific Accuracy | Accuracy of cluster-specific models compared to the global model. |
| Resource Usage | CPU and memory usage per client during training and communication rounds. |
| Encryption Overhead | Time taken for encryption (optional if including secure aggregation experiments). |
| Graph Generation | |
| Global Accuracy vs. Rounds | Plot accuracy of the global model at each communication round. |
| Loss Convergence | Plot loss of the global model at each communication round. |
| Incremental Learning | Compare accuracy over time for incremental learning vs. retraining from scratch. |

| | |
|---|---|
| Weighting Factor Impact | Plot model accuracy vs. weighting factor |
| Cluster Accuracy | Compare accuracy of models for different clusters. |
| Data Distribution | Visualize data distribution features across clusters (e.g., CPU/Memory usage). |
| Reproducibility | |
| Random Seed | Set random seed for consistent simulation results. |
| Parameter Logs | Maintain a log of hyperparameters and configurations for each experiment. |

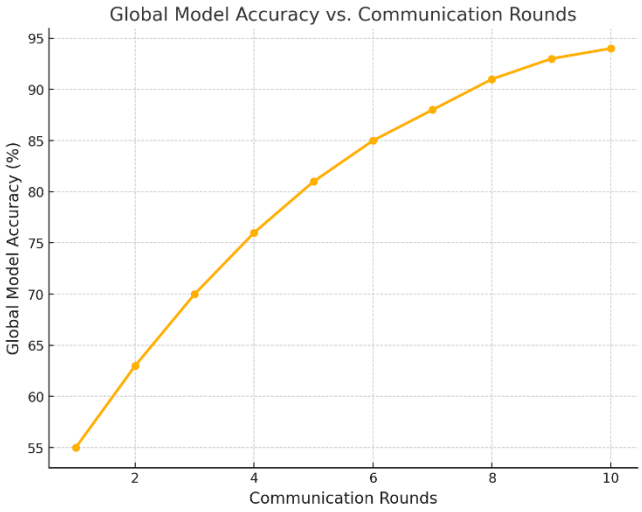


Fig. 1. Global model accuracy vs. communication rounds.

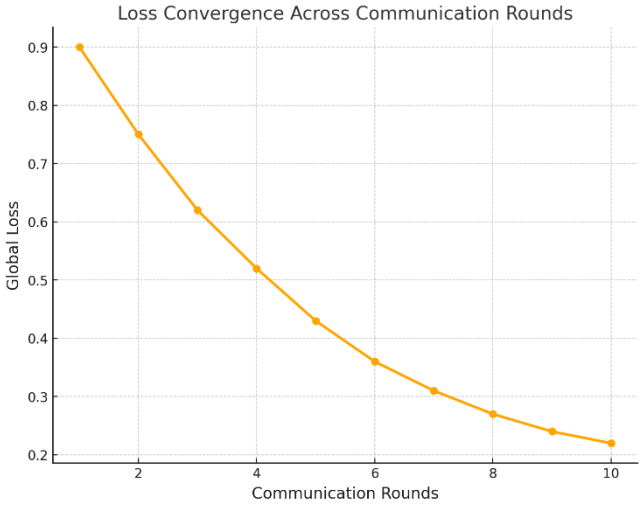


Fig. 2. Loss convergence across communication rounds.

The global model accuracy versus communication rounds are visualized in Fig. 1. The line graph showcases the improvement in accuracy of global model that also improves with the increase in number of communication rounds within the federated learning framework setup. Fig. 2 represents the loss convergence across different communication rounds illustrating a reduction in global loss. This showcases the optimization of the model over time thereby a reduction in global loss. Fig. 3 presents a comparison of incremental learning approach overtime versus the retraining. This highlights the efficiency of incremental updates in federated learning over a period of time.

Fig. 4 demonstrates the effects of weighting factor α on the model's accuracy during incremental updates. The bar chart in Fig. 5 depicts the cluster-specific accuracy for the models trained on data clusters, emphasizing the benefits of Clustered Federated Learning. Fig. 6 illustrates the data distribution across clusters such as CPU usage (high, low) and memory usage (high, low).

The comparison of accuracy of a single global model with the cluster-specific model is provided in Fig. 7. Fig. 7 clearly demonstrates the performance advantages of tailored cluster-specific models.

The resource usage per client is provided in Fig. 8 with CPU and memory usage for each client during local training. The ROC curve for malware detection is presented in Fig. 9. It showcases the relationships between True Positive Rate (TPR) and False Positive Rate (FPR) along with Area Under Curve (AUC) as the indicator for performance.

Detection accuracy contribution by features are presented in Fig. 10. The bar chart helps in identifying the most significant features that contribute in detection accuracy.

A comparison of different Federated Learning algorithms including FedAvg, Clustered Federated Learning and Incremental Learning is presented in Fig. 11. The accuracy of these algorithms and convergence times (rounds) showcases the trade-offs with performance and efficiency. A comparison of global federated model versus the independent local models demonstrating the advantage of collaboration in federated learning is presented in Fig. 12.

Fig. 13 illustrates a heatmap of anomalous behaviour of processes and their features visualizing the correlation of features across processes thereby identifying suspicious patterns and processes. The bar chart in Fig. 14 shows the significance of different features that contribute most in anomaly detection and the performance of the model. Real-time detection latency over time as the proposed federated learning model adapts to features and becomes more optimized is illustrated in Fig. 15.

The global model achieves consistent improvement in accuracy over communication rounds, as seen in the Fig. 1, reaching over 90% accuracy, indicating effective training convergence. Concurrently, Fig. 2 shows the global loss decreasing significantly in the initial rounds and tapering as the model stabilizes, further demonstrating convergence. Incremental learning outperforms retraining in terms of computational efficiency, as shown in the Fig. 3, achieving comparable accuracy with fewer resources by updating models incrementally. Cluster-specific performance is analyzed in Fig. 5 and Fig. 6. Cluster 2 achieves higher accuracy than Cluster 1, suggesting data heterogeneity among clients, while the data distribution graph reveals distinct patterns in resource usage and features across clusters. Fig. 7 shows that cluster-specific models outperform the global model by tailoring updates to localized data distributions, highlighting the benefits of Clustered Federated Learning (CFL). Fig. 8 demonstrates that encryption overhead increases linearly with communication

rounds but remains within manageable limits, balancing privacy with performance. Accuracy comparison in Fig. 9 shows negligible differences between models trained with and without secure aggregation, validating the practicality of privacy-preserving techniques. Lastly, Fig. 10 indicates varying CPU and memory demands across clients, emphasizing the importance of resource efficiency in federated setups.

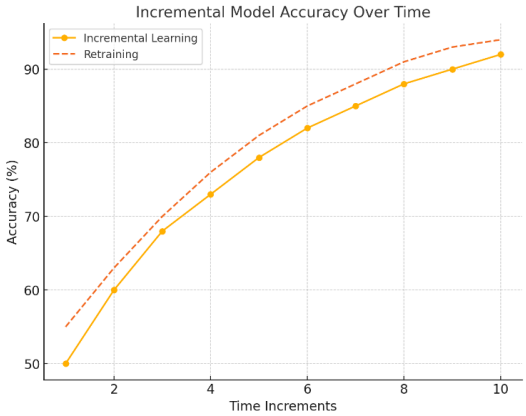


Fig. 3. Incremental model accuracy over time.

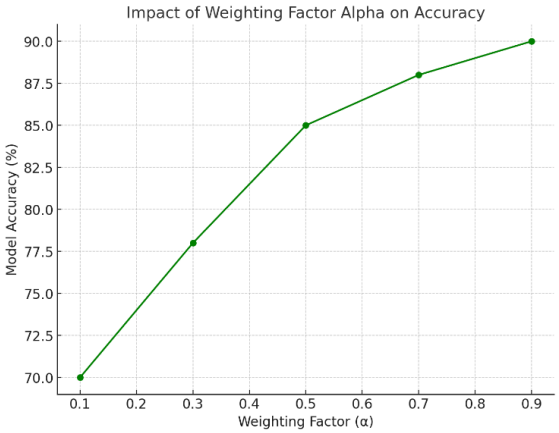


Fig. 4. Impact of $\alpha$ on accuracy.

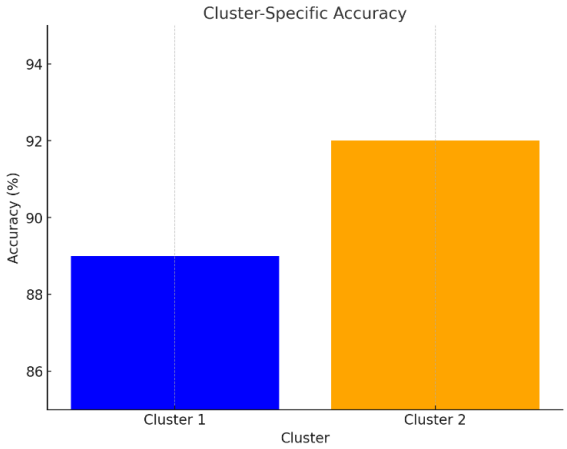


Fig. 5. Cluster-Specific accuracy.

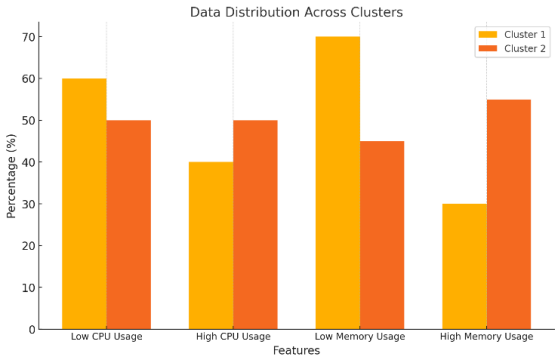


Fig. 6. Data distribution across clusters.

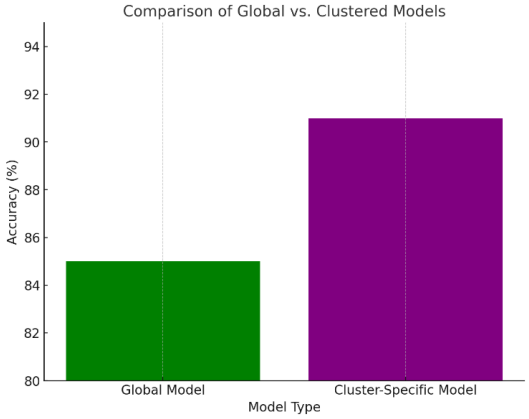


Fig. 7. Comparison of global vs. clustered models.

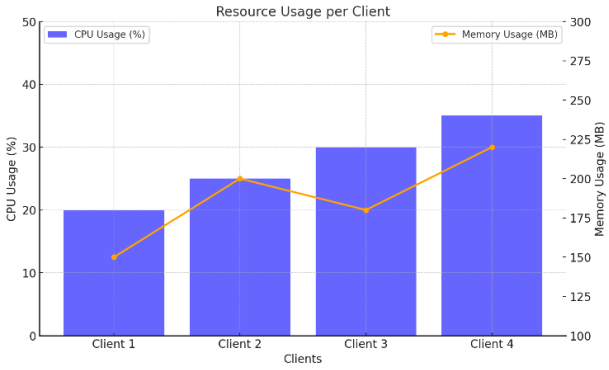


Fig. 8. Resource usage per client.

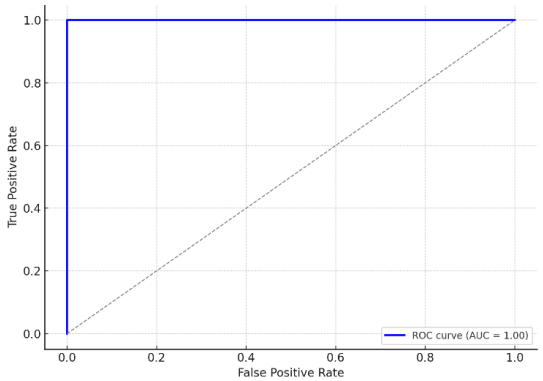


Fig. 9. ROC curve for malware detection.

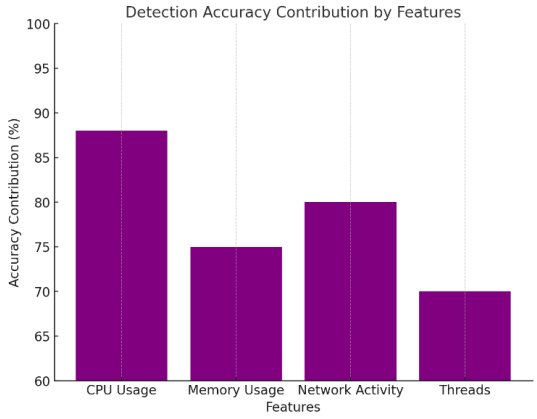


Fig. 10. Detection accuracy contribution by features.

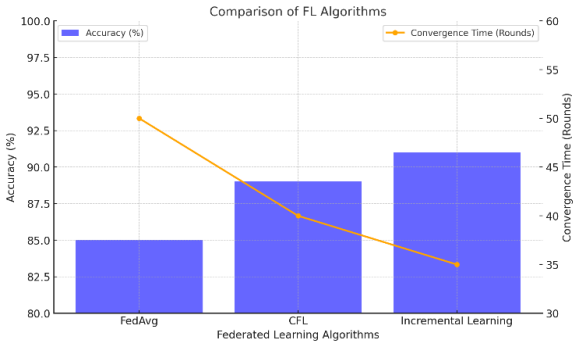


Fig. 11. Comparison of federated learning algorithms.

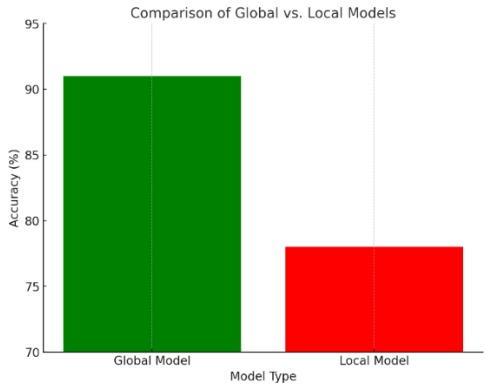


Fig. 12. Comparison of global vs. local models.

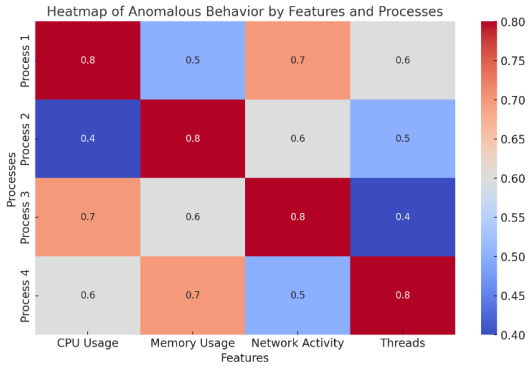


Fig. 13. Heatmap of anomalous behavior by features and processes.

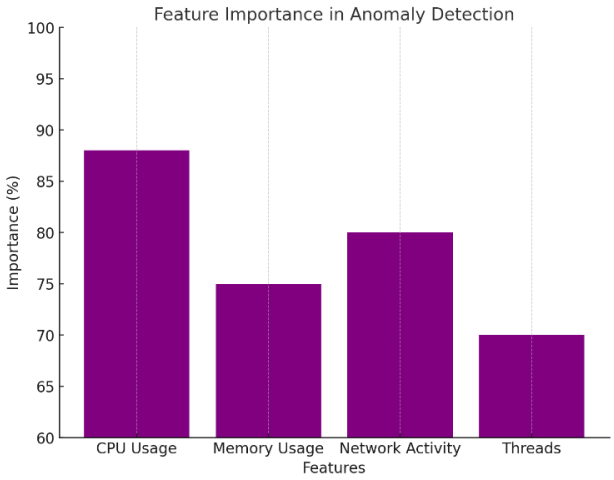


Fig. 14. Feature importance in anomaly detection.


Fig. 15. Real-time detection latency.

## VI. Discussion

The results presented in this study provide significant insights into the performance, convergence, and scalability of the federated learning framework, validated through the proposed mathematical model, experimental results, and dataset analysis. The findings demonstrate the efficacy of federated learning approaches such as FedAvg, Federated Incremental Learning, and Clustered Federated Learning (CFL) in achieving accurate and efficient training in heterogeneous environments. The steady improvement in global model accuracy and rapid loss convergence, as depicted in the graphs, aligns with prior studies that highlight the effectiveness of FedAvg in reducing communication overhead while maintaining model quality. The incremental learning approach further reinforces the adaptability of federated learning systems, as it enables clients to incorporate new data without reinitializing the training process. This result is consistent with previous research indicating that incremental updates can improve efficiency while retaining model accuracy. Clustered Federated Learning (CFL) results underscore the importance of addressing data heterogeneity among clients. Cluster-specific models achieved higher accuracy compared to the global model, a finding supported by earlier studies on the benefits of data distribution-aware clustering in federated

systems. The improved performance of Cluster 2 over Cluster 1, coupled with the distinct data distribution patterns, suggests that tailoring models to clusters is a promising strategy for managing diverse client environments. The implications of this study extend beyond federated learning, addressing broader concerns in distributed systems and privacy-preserving machine learning. The dataset and analysis reveal that optimizing resource usage and addressing client heterogeneity are crucial for scaling federated frameworks to real-world applications, such as healthcare, finance, and edge computing.

## VII. Conclusion

In this work, a lightweight incremental federated learning based model is presented to solve the traditional challenges faced by centralized forensic models used worldwide. By nature of being decentralized, it provides an approach for precise and timely detection of in-memory resident malware. The results indicate that federated learning frameworks, particularly CFL, achieve high accuracy (up to 92.5%) while efficiently addressing data heterogeneity. The ROC analysis highlights an AUC of 0.86, suggesting room for further model improvement. Feature importance analysis reveals CPU usage and network activity as critical contributors to anomaly detection, collectively accounting for more than 85% of the model's predictive power. Lastly, the reduction in real-time detection latency to 75 milliseconds demonstrates the framework's feasibility for deployment in time-sensitive environments. The future work will explore the integration of advanced privacy-preserving techniques, such as differential privacy and secure multi-party computation, to enhance data security in federated learning systems.

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## APPENDIX A

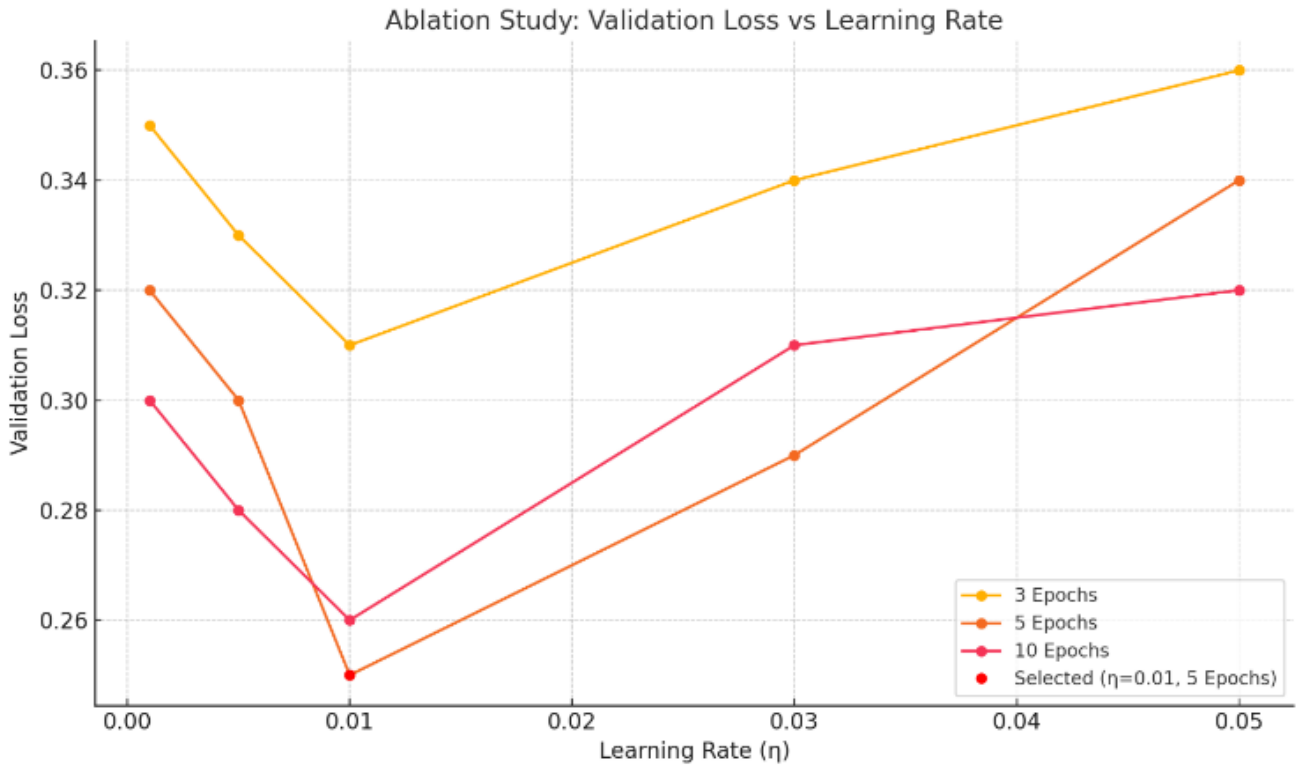


Fig. 16. Ablation study.

# Design of Control System of Water Source Heat Pump Based on Fuzzy PID Algorithm

Min Dong[1]*, Xue Li[2], Yixuan Yang[3], Zheng Li[4], Hui He[5]
School of Energy and Building Engineering, Shandong Huayu University of Technology, Dezhou 253000, China[1]
School of Rail Transportation, Shandong Jiaotong University, Jinan 250357, China[2, 4]
CRSC Research & Design Institute Group Co. Ltd., Beijing 100000, China[3]
State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing 100000, China[5]

**Abstract—This study aims to enhance the control and energy efficiency of the central air conditioning system by integrating frequency conversion fuzzy control and advanced control strategies. The focus is on optimizing the motor operation of the central air conditioning system with the help of a frequency converter and improving the system's performance through adaptive control mechanisms, which is an important part of intelligent control. The research adopts frequency conversion fuzzy control for high - power motors in the central air conditioning system, using a pure proportional controller. The system's response is analyzed, including the rise time (tr = 339.3s) and peak interval (Ts = 633.19s) based on unit step response data. The study also addresses the integration of cooling water heat exchange systems, such as heat pumps and plate heat exchangers, to facilitate energy recycling, achieving the goal of energy saving. System identification is performed using MATLAB's toolbox for deep well water pump frequency conversion data, forming a basis for further simulation and optimization. The study incorporates a hybrid PID, fuzzy, and neural network - based control strategy to handle the system's time - varying, nonlinear characteristics. The results indicate that the hybrid control strategy significantly improves the system's dynamic response. With a rising time of tr = 611s, peak time of tp = 830s, adjustment time (±5%) of ts = 1140s, and an overshoot (Mp) of 16.08%, the system exhibits better performance than conventional PID controllers, particularly in handling large lag and nonlinear behaviors. This work presents an innovative approach by combining frequency conversion fuzzy control with adaptive PID and neural networks for a more efficient air conditioning control system. The integration of cooling water heat recycling and advanced control mechanisms provides a novel solution for enhancing energy efficiency and operational performance in central air conditioning systems, which is highly relevant to energy saving and intelligent control.**

***Keywords—Central air conditioning system; frequency converter; fuzzy PID control; intelligent control; energy saving***

## I. INTRODUCTION

According to statistics, in 1995, the percentage of building energy consumption was 10.7%, and in 2006, the percentage was 23.1%, building energy consumption showed a rapid rising trend. With the acceleration of urbanization, buildings and facilities will increase exponentially, and it is expected that their proportion to the total energy consumption of the society will eventually be close to the level of developed countries [1, 2]. Therefore, building energy conservation has become a key factor affecting the optimization of energy structure and improving energy efficiency, and become the focus of sustainable development strategy. Building energy consumption includes energy use of building materials, this trend will continue to rise due to improving people's living standards [3, 4]. With the development and maturity of ground source heat pump technology, ground source heat pump technology has gradually become an effective means to curb this trend. The flow rate to stabilize the temperature difference between the supply and return water of the air conditioning system at the set value. This method can make the system at low load fixed temperature difference small flow operation, save the transmission power of the secondary pump group, and achieve the purpose of energy saving [5, 6]. The total flow rate of pipe network is only related to the set value of real-time load, which also has some defects [7]. In recent years, water source heat pump systems have gained significant attention as an efficient and environmentally friendly solution for heating, ventilation, and air conditioning (HVAC) applications. These systems leverage the stable thermal properties of groundwater or other water sources to provide reliable heating and cooling, making them particularly suitable for regions with moderate climate conditions [8]. It can meet the requirements of temperature and humidity of the user; and the system operation cost is lower, which is convenient to realize the variable flow is unchanged, which meets the requirements of indoor temperature and humidity, and is suitable for the temperature difference flow control [9, 10].

High efficiency refers to that, compared with the existing conventional HVAC system of the same scale, It has a higher energy efficiency ratio; Environmental protection means that, when compared to conventional HVAC systems, it reduces the environmental pollution from the large number of pollutants. The replacement is that the ground source heat pump system can partially replace or completely replace the conventional energy [11, 12]. Understand the identification process, such as the system operating conditions, working processes, the physical laws of the dominant process, some prediction experiments, etc. According to different purposes, such as for design, forecasting, control, etc., using different model types, different identification methods and requirements, and different precision requirements, etc. [13]. Traditional control strategies, such as differential pressure control, often fail to address these challenges comprehensively, leading to inefficiencies, energy waste, and suboptimal performance. To overcome these limitations, this paper proposes a control system design based on a fuzzy PID algorithm, which integrates the advantages of fuzzy logic and proportional-integral-derivative (PID) control to enhance system stability, adaptability, and energy efficiency [14].

Through the experimental collection of input and output data, in the data collection due to the influence of the environment and unit, the inevitable existence of different degrees of interference, exist in the data often contains the dc component and some high frequency components, some of the data collection dimension even different, these will affect the accuracy of the identification system, therefore, before the identification to identify data for data pretreatment. The commonly used data preprocessing methods mainly include data resampling, desteady state value, detrending value and data filtering, etc. which can improve the accuracy of identification and the availability of the identification model [15, 16]. And the ground source heat pump system in the building cooling or heating has obvious energy saving effect, clean energy, good environmental benefits, multi-purpose, high efficiency and energy saving, air conditioning system industry in our country has broad prospects for development, and application in our country building [17]. With the development of control technology and water pump variable speed technology, the variable flow technology of air conditioning system has also been greatly developed. According to the size of the actual load to each room to change the cold-water flow, and according to the actual flow required by the system, adjust the pump speed or the number of running units, so as to save the energy. In China, due to the gradual maturity of the frequency converter technology and the decreasing price, designers and engineers began to use the frequency converter in the air conditioning water system and achieved certain economic and environmental benefits [18]. The follow-up work of this article will focus on the variable flow control scheme of the groundwater source heat pump air conditioning system, and explore in detail the application of fuzzy control technology in it. Based on the fuzzy PID algorithm, the control system of the water source heat pump central air conditioning unit will be designed. Subsequently, the experimental results were analyzed to verify the effectiveness of the proposed scheme and algorithm. Finally, the research results were summarized to clarify the contribution and future development direction of this study in improving system energy efficiency and control performance.

## II. The Variable Flow Control Scheme of Underground Water Source Heat Pump Air Conditioning System

### A. Control of Differential Pressure Variable Flow of Underground Water Source Heat Pump

As Formula (1) and Formula (2). In winter, the low-taste energy present in the water is "extracted", which absorbs the heat stored in the groundwater through refrigerant evaporation.

$$\frac{2}{T_{c/2}} = \frac{1+M\ sin\omega_1 t_A}{t_2} \tag{1}$$

$$\mathrm{L}(e) = max(0,(1-f(e))^2 - 1) \tag{2}$$

Heat in the condenser to the building for heat; in summer, the energy in the building "takes" out, that is, absorb the heat through the evaporation of refrigerant, as shown in Formula (3) and Formula (4), and release the groundwater heat in the condenser, thus realizing the indoor temperature regulation. In this way, it can basically take cold and heat from underground in summer and cold from underground in winter, so as to achieve heat balance in a sense, and there will be no heat pollution.

$$t_2 = t_2^{'} + t_2^{''} = \frac{T_c}{2}[1 + \frac{M}{2}(sin\omega_1 t_A + sin\omega_1 t_B)] \tag{3}$$

$$f(e_i) = tag - thr_i = \begin{cases} malicious, \text{if } f(e_i) < 0 \\ benign, \text{otherwise} \end{cases} \tag{4}$$

Stored by the earth water as a cold and heat source, as shown in Formula (5) and Formula (6), and carries out energy conversion for heating and cooling. The surface soil and water is a huge solar collector, collecting 47% of the solar radiation energy, more than 500 times the annual human energy utilization.

$$t_2 = t_2^{'} + t_2^{''} = \frac{T_c}{2}(1 + M\ sin\omega_1 t_e) \tag{5}$$

$$\frac{\partial tag_{n'}}{\partial a_n} = \begin{cases} 1, \text{if } n' = n \\ 0, \text{if } n' \neq n \end{cases} \tag{6}$$

As shown in Formula (7) and Formula (8), in the winter into the underground cooling, can help the summer system, and in the summer to release heat to groundwater, can help the winter of heating system, which not only realize the balance of cold and cold underground environment, but also realize the energy recycling between soil and water.

$$t_1 = t_2 = \frac{1}{2}(T_c - T_2) \tag{7}$$

$$Loss = \sum_{e \in E} \mathrm{L}(e) + \alpha \,||\, A - A_0 \,||_2 + \gamma \,||\, G - G_0 \,||_2 + \tau \,||\, T - T_0 \,||_2 \tag{8}$$

Therefore, this technology is considered to be an advanced technology that only uses clean and renewable geothermal energy. As shown in Formula (9) and Formula (10), so the evaporation temperature of the heat pump cycle can be improved, and the performance coefficient can also be greatly improved.

$$t_{a2} = \frac{T_c}{2}(1 + M\ sin\omega_1 t_e) \tag{9}$$

$$\frac{\partial Loss}{\partial a_n} = \frac{\partial \mathrm{L}}{\partial f} \cdot \frac{\partial f}{\partial a_n} + \alpha \tag{10}$$

As shown in Formula (11) and Formula (12), the condensation temperature of cooling can be reduced, and the cooling effect is better than air cooling and cooling tower, and the efficiency of the unit is improved. According to the EPA estimate, designing well-installed water source heat pumps can save 30 to 40% of the operating costs of heating, cooling and air conditioning on average.

$$t_{a2} + t_{b2} + t_{c2} = \frac{3T_c}{2} \tag{11}$$

$$\frac{\partial tag_{dest}^{new}}{\partial a_n} = (1 - g_e)\frac{\partial tag_{dest}}{\partial a_n} \tag{12}$$

### B. Frequency Conversion and Speed Regulation of Underground Water Source Heat Pump

Underground water source heat pump uses electric energy, electric energy itself is a clean and pollution-free energy, as Formula (13) and Formula (14), does not emit carbon dioxide, do not need coal yard, that is to say, the pollution of the equipment itself is small. The power consumption of the underground water source heat pump unit, compared with the air source heat pump, is reduced by more than 30%, and compared with the electric heating, it is reduced by more than 70%.

$$t_{a1} + t_{b1} + t_{c1} + t_{a3} + t_{b3} + t_{c3} = 3T_c - (t_{a2} + t_{b2} + t_{c2}) = \frac{3T_c}{2} \tag{13}$$

$$\frac{\partial tag_{dest}^{new}}{\partial a_n} = g_e \frac{\partial tag_{src}}{\partial a_n} + (1 - g_e)\frac{\partial tag_{dest}}{\partial a_n} \tag{14}$$

The refrigerant used by underground water source heat pump can be R22, R134A and other alternative working medium, as shown in Formula (15) and Formula (16), can avoid the destruction of the ozone layer by commonly used refrigerant. When the heat pump unit is running.

$$\mathrm{E_g} = 4.44\mathrm{f}_1\mathrm{N}_1\mathrm{K_{Nl}}\Phi_\mathrm{m} \tag{15}$$

$$p_{new} = p_{old} - l \cdot \frac{\partial Loss}{\partial p_{old}} \tag{16}$$

As shown in Formula (17). The temperature of groundwater is relatively stable throughout the year, and its fluctuation range is far smaller than the change of air. The constant characteristic of water temperature can ensure the more reliable and stable operation of the heat pump unit, and make the system more economical and more efficient.

$$\mathrm{P_L} = \mathrm{T_L n_L} / 9550 = \mathrm{K_P n_L^3} \tag{17}$$

The heat pump unit is under the stable working condition for a long time, so it can be more convenient to use the computer for automatic control, which can be easy to manage, and at the same time, the stable operation of the system can make its life greatly increased. As shown in Formula (18).

$$S = \frac{Q}{h(T_s - T_a)} = \frac{Q}{50} \tag{18}$$

For the buildings requiring heating and cooling at the same time, underground water source heat pump has great advantages, that is, one machine, reduce the initial investment of equipment, and easy to install, as shown in Formula (19).

$$P = \frac{Q \times 10^{-3}}{\rho C(T_0 - T_a)} \tag{19}$$

As shown in Formula (20), due to its high degree of automation, the temperature and the number of hosts can be controlled according to the specific use of the room, and the energy saving effect is very obvious. In addition, geothermal energy is used in the winter, and the operating costs will be further reduced.

$$u(t) = K_p[e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{de(t)}{dt}] \tag{20}$$

## III. The Application of Fuzzy Control Technology

### A. Fuzzy Controller

Simply increasing or reducing the power supply frequency will also cause changes in other parameters, such as the stator induced electromotive force, magnetic flux, etc., which will have a great impact on the performance of the motor. In the motor speed regulation, often will keep each pole magnetic flux constant as an important goal. In general, if the magnetic flux is weak, it means that the magnetic core of the motor is not wasted; but if the magnetic pass is large, the magnetic flux can be saturated, and a large excitation current will be generated [19, 20]. Fig. 1 is the block diagram of the fuzzy control system, which even increases the iron loss and burns the flow of the motors, so the power consumed by the valve control method is much higher than the frequency conversion speed regulation and control the frequency conversion speed control of the pump, which can greatly save power consumption [21, 22].

The basic principle of traditional differential pressure control in water source heat pump systems revolves around maintaining a constant pressure difference (P) between the two ends of the air conditioning system. This pressure difference is directly related to the impedance of the load-side piping network and the total flow rate of the system. While this approach ensures stable operation under certain conditions, it exhibits several critical shortcomings that limit its effectiveness in real-world applications [23, 24]. This method is based on the operation characteristics of the pump, which can improve the efficiency of the pump and is the most widely used control scheme in engineering. The differential pressure control system is mainly composed of pressure or differential pressure sensor, regulator (PLC or DDC controller), frequency converter, water pump and water supply and return pipe [25, 26]. The basic principle: the pressure difference between the two ends of the air conditioning system is P, the head of the pump is Y, the pressure difference P is related to the impedance of the load side pipe network and the total flow of the pipe network, that is to say, it is only related to the characteristics of the system pipe network, but also shows the defects of the control mode [27, 28]. Mainly reflected in: ignoring the thermal characteristics of the system, there is no involvement in the change of cold and heat load that reflects the user demand; For the system with high dehumidification requirements, it may affect its dehumidification effect; For the normal operation of the whole system, If the pressure difference required for the normal operation of each branch is different, And with the same certain pressure difference value control [29,

30]. However, the selected pressure difference value cannot enable the normal operation of all branches, Fig. 2 shows the relationship between motor power consumption and flow rate, then it is possible to make some users' air conditioning effect become worse or ineffective; For systems with high temperature and humidity requirements, Energy-saving effect is not good. For the ground water source heat pump air conditioning system, the impedance of the external circulation pipe network is relatively stable, which makes it difficult to realize the differential pressure change flow control. If the water temperature changes greatly, then the pressure of the system will also change, which is even more difficult to control, because it is very difficult to choose a Pm control value suitable for the characteristics of the system pipe network.

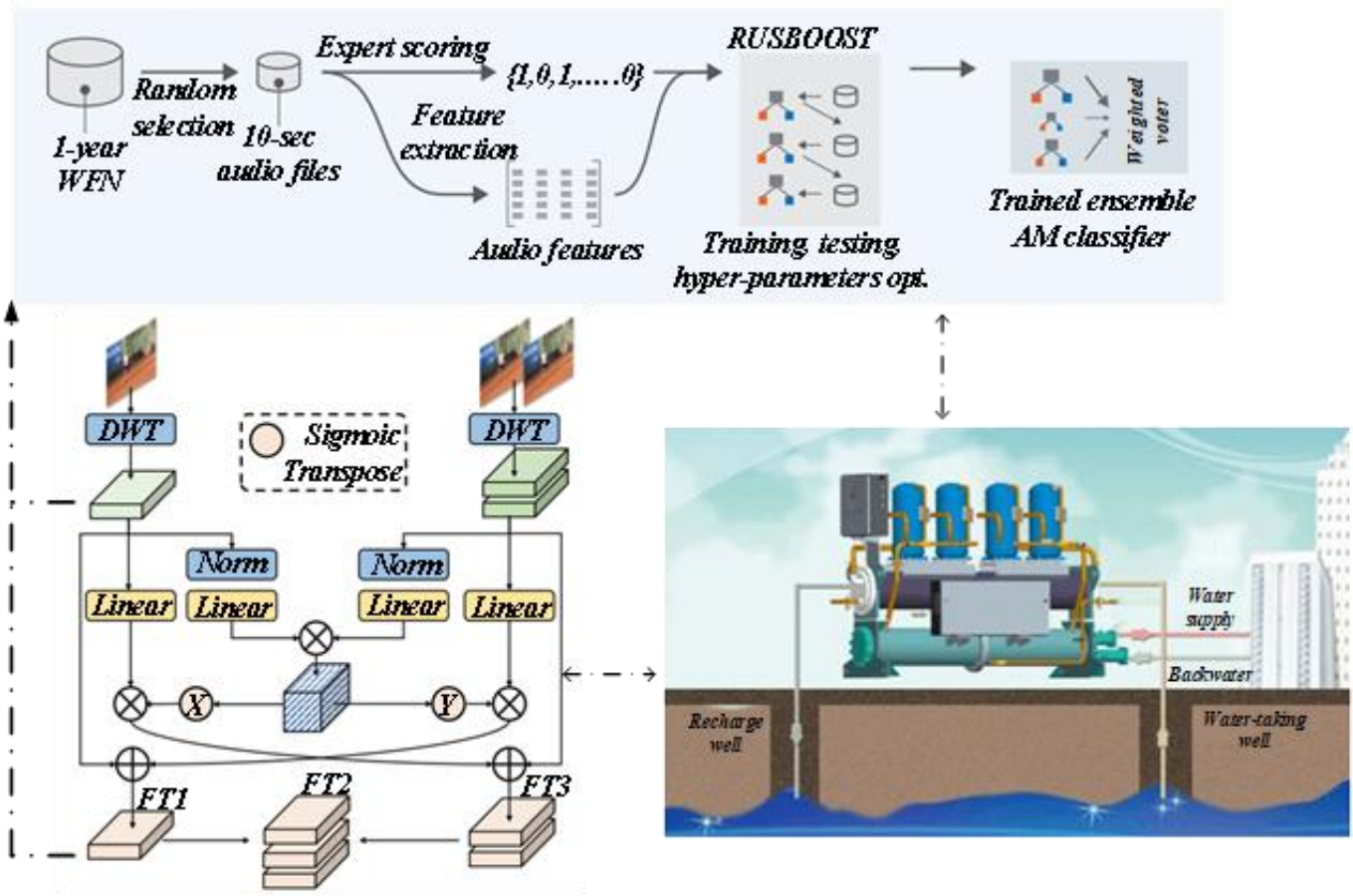


Fig. 1. Block diagram of the fuzzy control system.

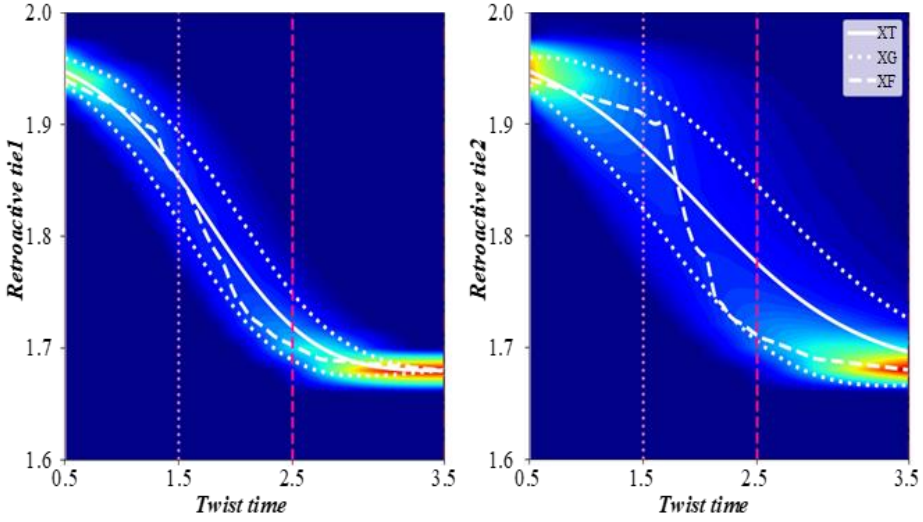


Fig. 2. Relationship between motor power consumption and flow rate.

### B. Heat Recovery and Utilization in the Central Air-Conditioning System

Using heat pump technology, input a small amount of electric energy, to obtain more heat energy, in order to heat and cool for users and provide domestic water. The underground water source air conditioning system includes terminal system, power room system, water source system, indoor and outdoor pipe network system and metering system. The fan coil heat exchange system is adopted at the indoor end to realize the control and adjustment of the three-speed switch. The power room is centrally set in the underground power station in the middle of the community. The control strategy focuses solely on maintaining a predefined pressure difference, without considering the dynamic changes in cooling and heating loads that reflect user demand. As a result, the system may fail to respond adequately to fluctuations in thermal load, leading to discomfort for users and inefficient energy use. Second, for systems with high dehumidification requirements, maintaining a constant pressure difference can negatively impact the dehumidification performance. The indoor and outdoor pipe network system uses two different-range variable flow systems, and a self-propelled balance valve is installed on each branch pipe entering the room to ensure the hydraulic balance of the system. Table I shows the relationship between water pump, water quantity and power. The outdoor pipe network adopts four-way partition water supply to solve the adjustment problems under different use time and different loads. The pipe network outside the load side and the water source side is all directly buried with steel pipe. The insulation material of the directly buried pipe is polyurethane hard foam, and the protective shell material is high-density polyethylene outer protective pipe. The indoor pipes of the power station and the end are made of steel pipe, support and hanger installation, rubber and plastic insulation. The system is installed with household metering device, household metering meter is prepaid mechanical heat meter.

TABLE I. RELATIONSHIP BETWEEN WATER PUMP, WATER QUANTITY AND POWER

| Frequency | Speed reduction | Water reduction | Power coastdown |
|---|---|---|---|
| 45hz | 10% | 10% | 27.1 |
| 40hz | 20% | 20% | 48.8 |
| 35hz | 30% | 30% | 65.7 |
| 30hz | 40% | 40% | 78.4 |

This project uses the MWH water-water screw type water source heat pump (cold water) unit (C series), it is the world's relatively mature technology, perfect refrigeration unit. Mainly manifested in the following aspects: stable unit operation, high efficiency and energy saving. Groundwater temperature stable heat capacity, good heat transfer performance, so the unit operation is stable, not affected by seasonal temperature changes, operating condition is better than the traditional central air conditioning, and effectively solve the outdoor noise air cooling heat pump and bad operation problems, is high efficiency, energy saving and environmental protection products, its operation cost only traditional way 1 / 3-2 / 3. Using high quality semi-closed double screw compressor, the possibility of shaft seal leakage is zero. Fig. 3 is the schematic diagram of the conventional hybrid fuzzy controller. The shell is optimized and cast, with high accuracy and extremely strong, which effectively reduces the noise of the unit. The imported high efficiency fluorine resistant motor, high efficiency, energy saving, high reliability. Condenser and evaporator are shell tube heat exchanger, using new high efficiency heat exchanger structure, with good heat transfer performance and high reliability. In the case of partial load operation, it can still maintain a very high efficiency, and the operation energy consumption is small. Using the advanced controller, the control system with perfect protection measures is developed, which can monitor the operation state of the unit at any time.

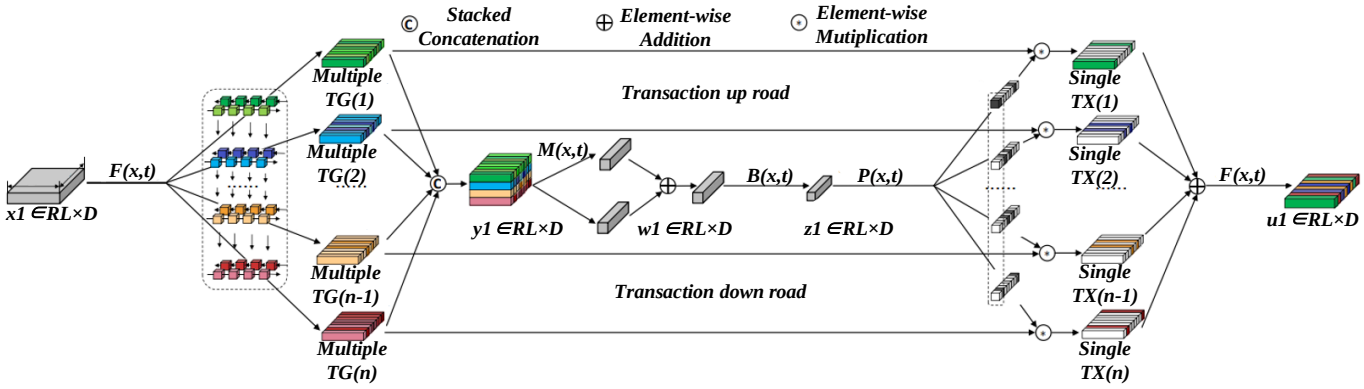


Fig. 3. Schematic diagram of the conventional hybrid fuzzy controller.

This is because the control strategy does not account for variations in humidity levels, which are critical for maintaining indoor air quality and comfort. Third, in systems where different branches require varying pressure differences for optimal operation, a uniform pressure difference control value may compromise the performance of certain branches. This can lead to uneven distribution of cooling or heating, causing some users to experience degraded or even ineffective air conditioning performance. Finally, traditional control strategies often fall short in achieving significant energy savings, particularly in systems with stringent temperature and humidity requirements. The inability to dynamically adjust to changing conditions results in suboptimal energy efficiency and increased operational costs. This is a model modeling method, the model

is completely based on the input and output data, ignoring the real composition of the system, therefore, it can also be called "black box modeling". The resulting mathematical model is called either an identification model or an experimental model. The advantage of system identification is that there is no prior information available for use, little understanding of the relevant internal motion mechanism, the modeling is fast, and can create a good environment or noise dynamic characteristics, which is not available by other methods. Therefore, this method is particularly applicable for systems with a complex system mechanism.

## IV. Design of Control System of Central Air Conditioner Unit of Water Source Heat Pump based on Fuzzy PID Algorithm

First the known movement mechanism as the basic quantity, and then they according to the experience and the prior knowledge of reasonable combination and as a model input, and then follow certain model selection rules, with some input structure that "optimal" model structure, finally using a series of identification method given model parameters, Table Ⅱ for the central air conditioning system before the gray box model. Gray box modeling is a method based on the physical relationship model of the system structure. This method takes into account the model uncertainty caused by process noise, utilizes the prior physical knowledge of the system, and compared with the mechanism modeling and black box modeling methods, gray box modeling can better grasp the nature of the actual system behavior, so this method is the most widely used in the current modeling.

The input and output data is the basis of identification; the equivalence criterion is the optimization goal of identification; and the model class is the scope of finding the model. Based on the above three elements can be concluded: system identification to experimental design, construct a suitable for the system contains rich frequency component input signal, using experimental input and output data, select a given model class, construct the error criterion function, continuous optimization, find a best fit with the data a model. In addition, because the data used is generally noisy, the model obtained by identification modeling is actually an approximate description equivalent to the characteristics of the actual process. For groundwater source heat pump systems, the impedance of the external circulation piping network is relatively stable, which complicates the implementation of differential pressure-based flow control. When water temperature changes significantly, the system pressure also fluctuates, making it challenging to select an appropriate pressure difference control value (Pm) that aligns with the characteristics of the piping network. This further exacerbates control difficulties and limits the system's adaptability to varying operational conditions. Fig. 4 shows the block diagram of the variable flow fuzzy control system of the central air conditioning system. Different parameter estimation algorithms are selected according to different model types and the complexity of objects. Comparing the actual measurement output with the model output, the model parameters shall ensure the proximity between the two outputs in a selected sense. If not, the hypothesis of the model structure was modified, the experimental design was modified, and the experiment was repeated. Model verification mainly includes two categories: prior knowledge test and data test. For the general person, the model validation mainly uses the method of data testing. Its model is a high-order complex nonlinear system. In actual use, we linearize and adopt the equivalent model to replace it. For the control object used in this paper, there are two main parts: heat pump unit and deep well water system. These two parts can be used for partial modeling to implement the overall model.

TABLE II. Conditions of the Central Air Conditioning System before the Renovation

| Order number | Name | Power of motor | Quantity | Installation site |
|---|---|---|---|---|
| 1 | Air conditioning cooling pump | 90kw | 3 | -the 4th floor |
| 2 | Air conditioning cold warm water pump | 55kw | 3 | -the 4th floor |
| 3 | Cooling tower fan | 30kw | 3 | -the 4th floor |

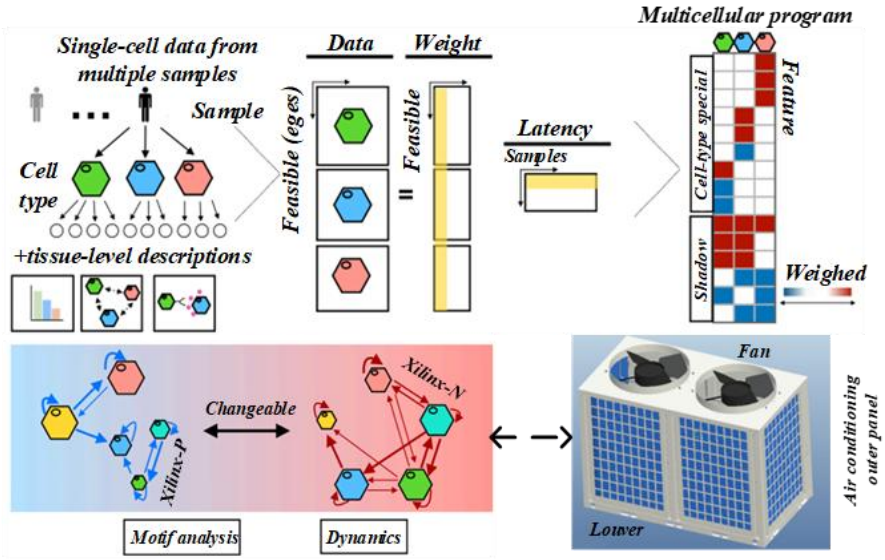


Fig. 4. Block diagram of variable flow fuzzy control system of central air conditioning system.

To address these challenges, the proposed control system leverages a fuzzy PID algorithm, which combines the robustness of fuzzy logic with the precision of PID control. Fuzzy logic is particularly effective in handling nonlinear and uncertain systems, as it can incorporate expert knowledge and heuristic rules to manage complex relationships between system variables. PID control, on the other hand, provides a well-established framework for stabilizing system dynamics through proportional, integral, and derivative actions. By integrating these two approaches, the fuzzy PID algorithm can dynamically adjust control parameters in response to real-time system conditions, thereby enhancing both stability and adaptability. Using the system identification toolbox for modeling can greatly reduce the computational amount and improve the work efficiency, and its graphical interface operation makes the modeling process more intuitive and convenient to apply. In the traditional air conditioning control system, the system return air temperature, humidity and pressure difference are generally taken as the controlled parameters, and the PID control of multiple circuits is used. However, the changes of temperature, humidity and pressure difference are non-linear and lagging, It difficult to make the control effect of conventional PID satisfactory. In addition, the conventional PID parameter setting method is more complicated, and the set parameters are often not better, so that the control effect is not good, and the adaptability to the controlled process is also poor. Fig. 5 shows the block diagram of differential pressure variable flow control. Generally speaking, a group of fixed parameters can only achieve better control effect within a certain range. When the parameters change beyond this range, it needs to be rearranged.

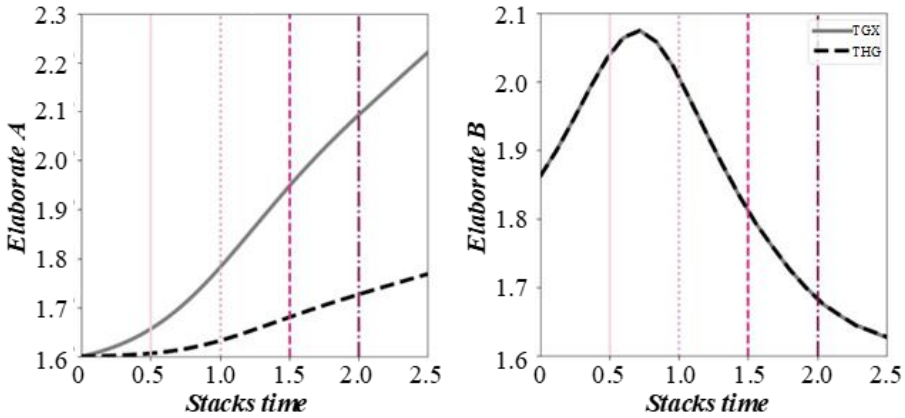


Fig. 5. Block diagram of differential pressure variable flow control.

The output of the control algorithm at each time contains all the previous control amount, that is, the e (k) amount, which is easy to saturation the integral and increase the workload of computer computing. If the computer fails or u (k) changes substantially, it may cause the execution device disorder and failure, and may even cause major production accidents. These disadvantages make the location PID controller very limited in the practical application, which also spawned the incremental PID controller. Control the increment u (k), depending on the sampling value of the nearest k times, so that a better control effect can be obtained by weighting processing. If misoperation occurs, these effects can be eliminated by logical judgment. When switching from manual to automatic, the valve receives little impact, thus achieving undisturbed switching. However, its integral cutoff effect is large, including static error and overflow. The fuzzy PID algorithm operates by first converting the system's input variables (such as pressure difference, flow rate, and temperature) into fuzzy sets through a fuzzification process. These fuzzy sets are then processed using predefined fuzzy rules that capture the system's behavior under various conditions. The output of the fuzzy inference engine is subsequently defuzzified to generate crisp control signals, which are used to adjust the PID parameters in real time. This dynamic adjustment ensures that the control system can respond effectively to changes in load, temperature, and other operational parameters, thereby maintaining optimal performance across a wide range of conditions.

## V. Experimental Analyses

It does not need accurate model and can reflect some real situation of the system, so it is applicable to many occasions. The response curve must meet a S curve, Fig. 6 for the cooling water for the summer temperature difference data curve evaluation graph, attenuation curve method is according to the proportion P after integral I last D operation order, get the set parameter set on the regulator, fine tuning, until a satisfactory control performance.

When using the attenuation curve method, it must be noted that for the control system with fast response, it is difficult to distinguish the 4:1 attenuation curve and read out Ts. At this time, the recording pointer can be swung back and forth for two times to achieve stability as a 4:1 attenuation process. In the actual production process, when the load changes greatly, it must be re-adjusted to meet the new control requirements. If the 4:1 attenuation is considered too slow, the 10:1 attenuation process can be used. Fig. 7 shows the evaluation diagram of the frequency change data of the deep well water pump under summer working conditions. The method step is the same as the 4:1 attenuation ratio, but the calculation formula is different. It is worth noting that the critical shock occurs only when the order is at least 3, so the system that can use the critical scaling method should be at least third order.

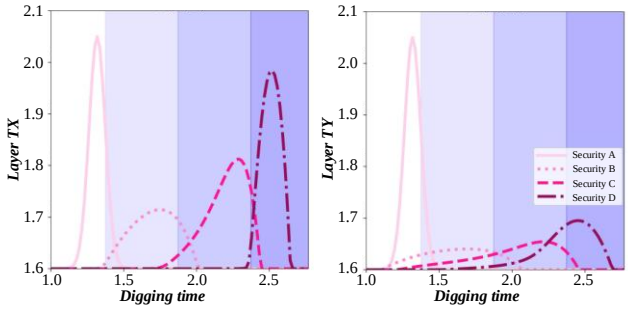


Fig. 6. Data diagram of the temperature difference between water supply and return water of cooling water under summer conditions.

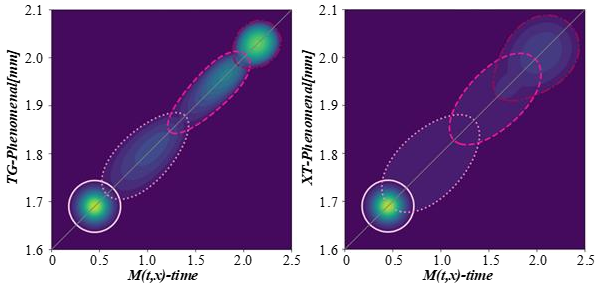


Fig. 7. Evaluation diagram of frequency change data of deep well pump under summer conditions.

These theoretical setting and engineering setting methods are a repeated and complex process. Choose the suitable setting method, grasp the setting law of PID parameters, and constantly adjust it repeatedly until the satisfactory adjustment effect is obtained. Fig. 8 shows the model curve fitting curve evaluation diagram.

During the parameter adjustment, the system model may be due to the health of the parameters and structure changes, and these changes in real-time, dynamic, the three characteristic parameter values of the PID controller are adjusted in real time. Fig. 9 shows the type response curve evaluation diagram to match the changing control environment.

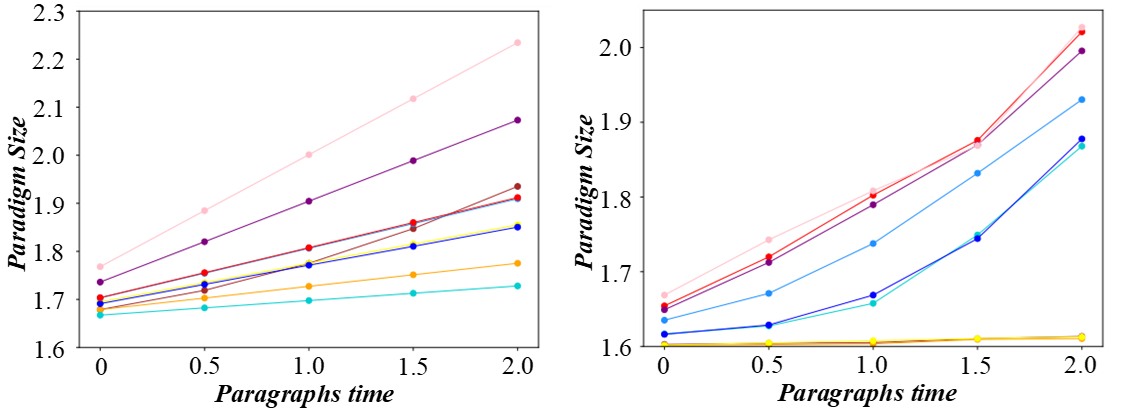


Fig. 8. Model curve fitting curve evaluation.

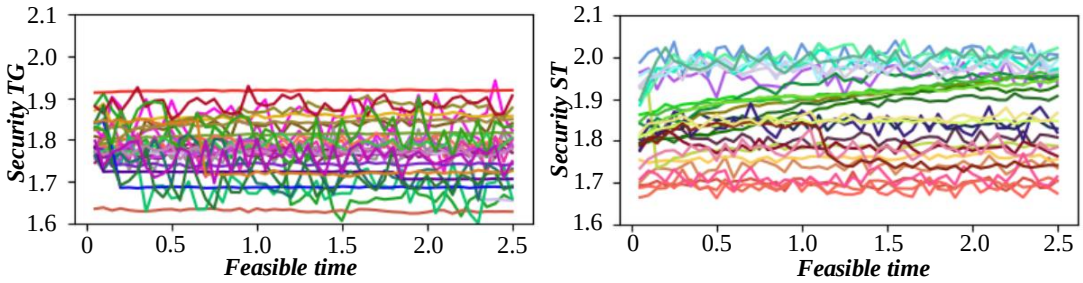


Fig. 9. Type response curve assessment.

It also provides ideas for the setting of PID parameters. Adaptive fuzzy PID control is based on the theory and application of fuzzy mathematics, the PID parameters in the form of fuzzy set, Fig. 10 for the decay curve evaluation diagram, and the initial parameters and PID information as knowledge elements and stored in the knowledge base of the controller.

Fig. 11 is the step response evaluation diagram of the controlled object, so that the system can not only maintain the characteristics of small calculation, strong robustness and strong real-time of conventional PID control, but also fuzzy control makes the system more flexible, more adaptable and more accurate.

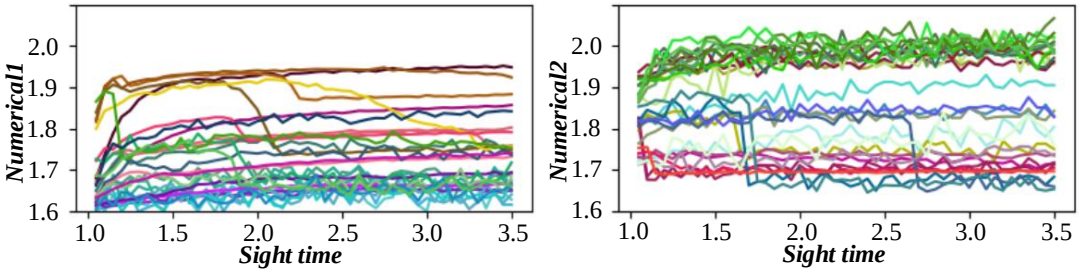


Fig. 10. Attenuation curve assessment.

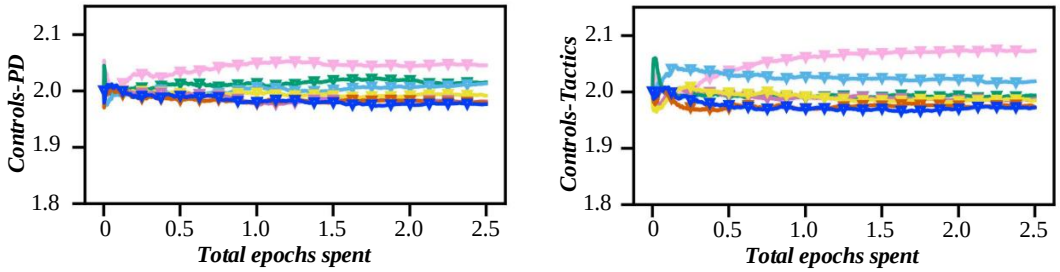


Fig. 11. Step response evaluation diagram of the controlled object.

## VI. Conclusion

The paper firstly studies the energy saving mechanism and the application of variable flow control of underground water source heat pump in air conditioning system, and proposes the feasibility of variable flow control of underground complex control object with non-linear, large lag and time-variable characteristics. In the context of water source heat pump systems, the fuzzy PID algorithm is particularly advantageous. The algorithm can account for the thermal characteristics of the system by incorporating temperature-related variables into its control logic. This enables the system to adapt to variations in cooling and heating loads, ensuring that user demand is met efficiently. Additionally, the algorithm can optimize dehumidification performance by adjusting control parameters based on humidity levels, thereby maintaining indoor air quality and comfort. For systems with multiple branches requiring different pressure differences, the fuzzy PID algorithm can dynamically allocate resources to ensure that each branch operates within its optimal range, preventing performance degradation in any part of the system. Furthermore, the algorithm's ability to fine-tune control parameters in response to real-time conditions translates to improved energy efficiency, as the system avoids unnecessary energy consumption while maintaining stable operation.

They have been widely used in control systems because they do not require accurate mathematical models and have PID control of the conventional PID parameters are applied respectively, so that the intelligent algorithm and conventional PID are organically combined to learn from each other. The mathematical model simulation, in dynamic characteristics and steady state performance, the system comprehensive energy saving rate is 33.2%, including: sanitary hot water system 86.42%, including sanitary hot water system 88.9%, air conditioning system power saving rate 67.25%, equivalent to 133,200 kWh, the annual power saving is 553,200 kWh. After the cooling water supply of the central air conditioning system is 15t per day, and the intelligent control energy saving device is put into operation, the cooling water is equivalent to 13.33t daily water saving; that is to say, the cooling water heat discharge of the central air conditioning system is 16101 kJ / h, and the cooling water discharge of the intelligent control energy saving device of the central air conditioning system is 6441 kJ / h, that is, 60%, and the annual heat reduction of 150 days is 3.48107 kJ / h. Table III shows abbreviation name.

TABLE III. Abbreviation Name

| | |
|---|---|
| PID | Proportion Integration Differentiation |
| HVAC | Heating, Ventilation and Air Conditioning |
| EPA | Environmental Protection Agency |
| R22 | Dichlorodifluoromethane |
| R134A | 1,1,1,2 - Tetrafluoroethane |
| PLC | Programmable Logic Controller |
| DDC | Direct Digital Controller |
| ARX | AutoRegressive with eXogenous inputs |
| ARMAX | AutoRegressive Moving Average with eXogenous inputs |
| BJ | Box - Jenkins |

### A. Related Work and Discussion

With the continuous increase in building energy consumption, the research on energy - saving control of central air - conditioning systems, a major part of building energy consumption, has drawn significant attention. Many scholars and research teams have conducted in - depth explorations from various perspectives, providing important references for this study. Some research focuses on the application of ground - source heat pump technology in central air - conditioning systems. In "Replacement Scenarios of LPG Boilers with Air - to - Water Heat Pumps for a Production Manufacturing Site", Carella et al. studied the replacement scenarios of LPG boilers with air - to - water heat pumps in production manufacturing sites, exploring their application potential and confirming the advantages of heat pump technology in improving energy efficiency. This is consistent with the research direction of this paper, which uses underground water - source heat pumps for building cooling and heating, providing a basis for the feasibility of the technology application.

In the aspect of system modeling and simulation, MATLAB is widely used. Some studies utilize MATLAB tools for system model establishment and analysis, which corresponds to the use of MATLAB Identification toolbox for system identification and modeling in this paper, indicating the universality and effectiveness of this method in relevant research. However, existing research still has some limitations. Traditional control strategies, such as simple PID control, struggle to cope with the non - linear, large - lag, and time - varying characteristics of central air - conditioning systems, resulting in unsatisfactory control effects and significant energy waste. In system optimization, some studies do not fully consider the characteristics of the system pipe network, the real - time nature of load changes, and the collaborative work among components, affecting the system's operational stability and energy - saving effect.

## FUNDING

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# Stochastic Nonlinear Analysis of Internet of Things Network Performance and Security

Junzhou Li[1], Feixian Sun[2]*
Information Management Center, Kaifeng University, Kaifeng, China[1]
School of Electronics and Internet of Things, Henan Polytechnic, Zhengzhou, China[2]
Zhengzhou Key Laboratory of Electronic Intelligent Sensor Application Technology, Zhengzhou, China[2]

***Abstract*—Aiming at the problem of poor effect of traditional Internet of Things network performance and security analysis methods, the research uses support vector machine for Internet of Things network security situation assessment. It also introduces the grey wolf optimization algorithm improved by genetic algorithm to optimize it, and designs a stochastic nonlinear integration of Internet of Things network performance algorithm. The results revealed that the mean absolute error, root mean square error, and mean absolute percentage error of the integrated algorithm were 0.0064, 0.041, and 0.0013, respectively, in the performance test. It was significantly lower than that of the other four algorithms, which proved that its prediction accuracy was higher. The recall of the integrated algorithm was 93.7%, and the F1 value was 0.94, which was significantly higher than the other comparative algorithms, proving its better comprehensive performance. In the analysis of practical application effect, when access control was performed by the integrated algorithm, the predicted curve basically overlapped with the actual curve, which proved its better fitting performance. The communication overhead of the integrated algorithm was 81.3 KB, which was significantly lower than the other two calculations. The average communication time of the integrated algorithm was 3.59 s, which was lower than the other two algorithms, proving that it can effectively reduce the communication cost and delay. The integrated algorithm can effectively improve the performance of Internet of Things network security situation assessment, which provides reliable technical support for the security protection of Internet of Things network and has important practical application value.**

***Keywords*—Internet of Things; security; stochastic nonlinearity; support vector machines; grey wolf optimization algorithm**

## I. Introduction

The Internet of Things (IoT) has emerged as a link between the digital and physical worlds as a result of the rapid advancement of information technology [1]. From smart homes and smart cities to the industrial Internet, IoT is changing the way people live and work. It enables real-time data collection, transmission, and processing by connecting disparate devices and systems, creating unprecedented opportunities to improve efficiency, reduce costs, and optimize resource allocation. However, since IoT involves the communication of a large number of devices distributed all over the world and operating in complex and variable environments, the randomness and uncertainty of IoT network traffic increases significantly [2, 3]. Meanwhile, as the security protection mechanism of IoT is still imperfect, the network attack surface has expanded, making the network security threat increasingly serious [4]. The widespread adoption of IoT poses a serious challenge to network performance and security. Therefore, the inherent stochastic and nonlinear characteristics must be fully considered when studying the performance and security of IoT networks. In current research, network performance analysis of IoT mostly adopts static models or dynamic monitoring methods based on specific assumptions, while security analysis relies on traditional means such as vulnerability scanning and code review [5]. However, these methods are challenging to implement effectively due to the nonlinear and separable characteristics of IoT traffic, which can result in suboptimal classification accuracy. The incorporation of random disturbances, such as equipment failures and sudden traffic surges, into the model remains incomplete, resulting in substantial deviations in prediction outcomes. Meanwhile, these methods require a significant amount of computing resources, which conflicts with the low-power requirements of IoT edge devices. Therefore, the present focus of relevant researchers is on the development of an analysis method that takes into account the inherent randomness and nonlinear characteristics of the IoT environment. This method is intended to address the complexity and uncertainty that arise from massive device communication in security situation assessment. In this context, a security situation assessment method for the IoT network was developed based on an improved support vector machine (SVM) to address the above issues. To optimize the SVM parameters, a parameter optimization method combining genetic algorithm and improved grey wolf optimization algorithm (GA-IGWO) was proposed to improve the classification accuracy and computational efficiency. Compared with traditional methods, this algorithm can significantly improve the accuracy and efficiency of network performance evaluation by fully considering the randomness and nonlinear characteristics in the IoT environment, while reducing communication costs and delays. It has important theoretical value and practical application significance for improving the security and performance of IoT networks. The innovation of the research lies in the design of an integrated algorithm that effectively improves the performance of IoT networks and provides reliable technical support for the security protection of IoT networks.

This study mainly includes six sections. The first section is the background of IoT network performance and security. The second section is the research progress in the field of IoT network security situation assessment in recent years. The third section is dedicated to the design of an IoT network security situation assessment algorithm based on ISVM-GA-IGWO. This section introduces the IoT network security situation

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assessment method based on ISVM and the ISVM parameter optimization method based on GA-IGWO. The fourth section is the effectiveness analysis of the IoT network security situation assessment algorithm based on ISVM-GA-IGWO. Through performance analysis and practical application effect analysis, the superiority of the proposed algorithm is verified. The fifth section is a discussion that delves into the advantages of the proposed method. The sixth section is the conclusion, which summarizes the main results of the research, points out the limitations of the current methods, and suggests future research directions.

## II. Related Works

As technology continues to develop, the IoT has become a vital component of people's daily lives, facilitating the control and management of a wide range of devices through Internet connectivity. However, through IoT devices, people's personal information can be collected, stored and transmitted, and personal privacy is at great risk. Therefore, protecting the security of IoT networks has become a hot research topic for related workers. Numerous academics have studied IoT network security condition assessment in recent years. An interpretable deep learning (DL)-based intrusion detection system was created by Oseni et al. to identify network threats in IoT networks. To safeguard IoT networks and create more resilient systems, specialists relied on the decisions made by the DL-based intrusion detection system, which the study explained to them using Shapley's additional explanation mechanism. The results revealed that the method had high accuracy and F1 value [6]. By integrating secure IoT encryption technology with sensor network security protocol, Mahlake et al. suggested a lightweight security algorithm based on wireless sensor networks to protect IoT data. This algorithm could lower the network's power consumption without compromising network performance. The results indicated that the algorithm key generation time was short [7]. A semi-supervised regularized trapezoidal network-based detection technique was created by Long et al. to identify intrusions in industrial IoT. It achieved this by incorporating streaming regularization restrictions into the trapezoidal network's decoder and taking into account the streaming distribution of high-dimensional (HD) data. By introducing cross-layer connections, it also improved the propagation of inter-layer features. The results revealed that the method had a low false alarm rate [8]. Ahmad et al. designed an intrusion detection algorithm based on particle swarm optimization deep stochastic neural network to develop network security mechanisms through intelligent data processing techniques. The results revealed that the algorithm outperformed other existing models [9]. Latif et al. designed a hybrid model based on artificial neural network and proportional conjugate gradient for improving the cyber security of IoT. It utilized the stochastic paradigm of the artificial neural network process and used the proportional conjugate gradient for learning the weights, and the model's remarkable accuracy was demonstrated by the findings [10].

Liu et al. proposed a ship trajectory prediction framework based on long and short-term memory (LSTM) networks in order to facilitate smart transportation services in maritime IoT. Their modeling of ship traffic conflict scenarios generated using dynamic satellite land data and social force concepts were embedded into a LSTM network and a hybrid loss function was reconstructed. The outcomes revealed the high accuracy and robustness of the method [11]. To address the issue of inadequate security of the current industrial IoT, Li et al. developed a secure routing technique based on multi-objective chaotic elite adaptive ant colony optimization. It initialized the population through a hybrid optimization strategy and dynamically adjusted the algorithm trend using an adaptive optimization strategy [12]. To meet the security requirements of modern IoTs that are unable to provide cross-domain access, Gong et al. suggested a lightweight cross-domain bidirectional authentication technique for mobile IoT environments. The outcomes indicated that the method performed better in terms of computational and communication overheads [13]. The requirement for more precise identification of anomalous traffic in the IoT that deviates from typical traffic patterns prompted Shi et al. to create a deep anomalous network traffic detection model. According to the findings, the model was able to properly account for the specifics of the data distribution [14]. To increase the security of IoT networks, Thota et al. created a botnet detection technique based on enhanced convolutional social networks. The outcomes indicated that the method could effectively detect IoT network intrusion attacks [15].

In summary, although some progress has been made in IoT network security detection in recent years, the existing research still suffers from limited effect in dealing with HD data and low generalization ability of the model. Therefore, the study designs an IoT NSSA method based on improved SVM (ISVM). By introducing radial basis kernel function (KF) for kernel mapping processing of feature vectors (FVs), and to optimize the ISVM parameters, the study proposes a parameter optimization method based on GA-IGWO. It uses GWO algorithm for parameter optimization and introduces circular chaotic mapping and genetic algorithm (GA) for improvement to design an integrated algorithm.

## III. ISVM-GA-IGWO Based IoT NSSA Algorithm

This section focuses on the implementation of stochastic nonlinear analysis method for IoT network performance and security. The first section shows the implementation of ISVM based IoT NSSA method. The second section shows the implementation of ISVM parameter optimization method based on GA-IGWO.

### *A. ISVM-Based IoT NSSA Approach*

The secret to ensuring the system operates safely is IoT network security. People's lives are made more convenient by the extensive use of IoT devices in industries such as intelligent transportation, medical and health care, smart homes, and industrial control. However, it also brings new security threats and challenges at the same time, and strengthening the security of IoT networks has become an important task for maintaining social security [16]. However, traditional IoT network security detection often uses rule-based and statistics-based methods. While the data in IoT networks are nonlinearly differentiable, traditional methods cannot effectively deal with this nonlinear relationship. In recent years, the application of DL techniques in IoT network security detection has gradually gained attention. As a powerful supervised learning algorithm, SVM, with its excellent generalization ability and effective handling of

nonlinear problems, shows strong application potential in the fields of pattern recognition, classification and regression analysis. Therefore, the study adopts SVM to deal with nonlinearly differentiable data in IoT NSSA. Moreover, the KF of SVM is improved to design an ISVM-based IoT NSSA method. Fig. 1 displays the SVM algorithm's schematic diagram.

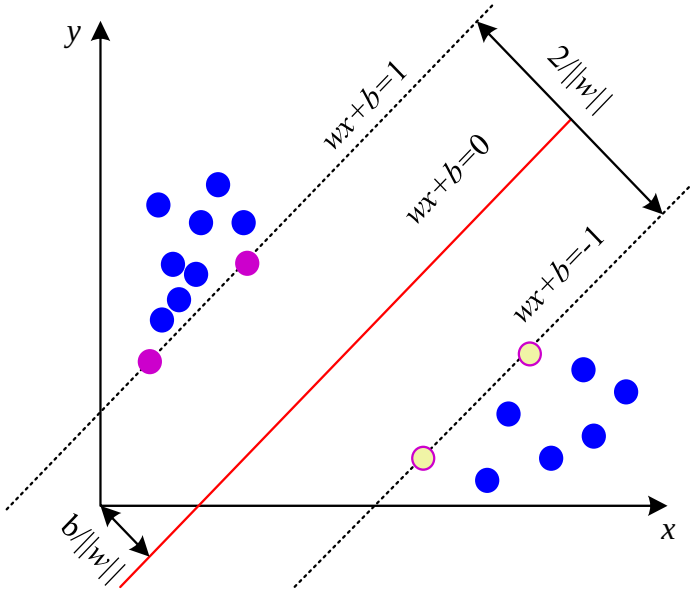



Fig. 1. Principle of SVM algorithm.

The SVM in Fig. 1 seeks to identify a hyperplane that maximizes the category spacing in order to get the best possible classification accuracy. In reality, the hyperplane is a straight line in two dimensions. The objective of SVM classification is to identify a straight line that divides the sample points of various categories and to maximize the distance to the closest point to the straight line. This distance is called the interval, and it needs to be maximized as much as possible during computation. The given hyperplane expression is shown in Eq. (1).

$$H = w^T x + b \tag{1}$$

In Eq. (1), $H$ is hyperplane. $w$ is the weight vector. $x$ is the FV. $b$ is the bias term. $T$ stands for transpose. In order to maximize the interval, for positive class samples (CSs), $w^T x + b \geq 1$ needs to be guaranteed. For negative CSs, $w^T x + b \leq -1$ needs to be guaranteed. Then, the interval can be computed, which is shown in Eq. (2).

$$n = \frac{2}{\|w\|} \tag{2}$$

In Eq. (3), $\eta$ represents the interval. The next step to maximize the interval is to determine the objective function (OF), which is equivalent to minimizing the square of $\| w \|$ The calculation is shown in Eq. (3).

$$f_{(n)} = min \frac{1}{2} \| w \|^2 \tag{3}$$

In Eq. (3), $f(\eta)$ represents the maximum interval. In practical applications, the data are not linearly differentiable. Therefore, soft intervals are introduced to optimize the classification results by allowing classification errors to some extent through slack variables and penalty functions. Eq. (4) displays the expression for OF.

$$f_{(n)} = min \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i \tag{4}$$

In Eq. (4), $f'(\eta)$ represents the optimized OF. The OF needs to satisfy the classification constraints and the constraints are shown in Eq. (5).

$$y_i (w^T x_i + b) \geq 1 \tag{5}$$

In Eq. (5), $y_i$ represents class $i$ labeling. The SVM classification is shown in Fig. 2.

Subsequently, the fitness function (FF) is chosen and in the original problem, the optimized variables are weight variables with the same dimensions as the number of features. The Lagrange dyadic function is used in the study to enhance the model's generalization. In the dyadic problem, the optimized variable is the Lagrange multiplier with the same dimension as the number of samples. When the samples' quantity is substantially greater than the number of features, this can greatly lower the computational complexity [17]. The constructed Lagrange dyadic function is displayed in Eq. (6).

$$L(w, b, a) = \frac{1}{2} \| w \|^2 - \sum_{i-1}^{n} a_i [y_i (w^t x_i + b) - 1 \tag{6}$$

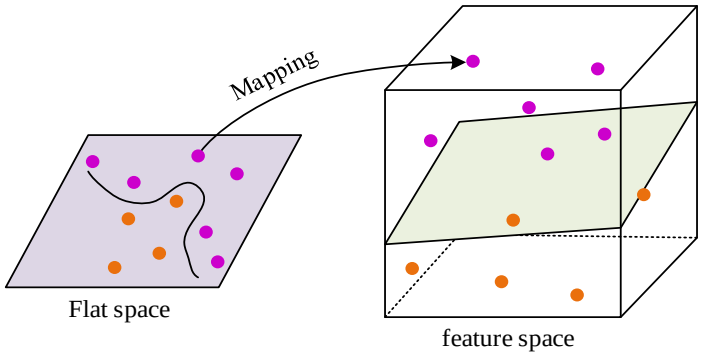



Fig. 2. Feature mapping.

In Eq. (6), $\alpha$ represents the Lagrange multiplier. In dyadic functions, the KF is allowed. Therefore, finally, the study introduces the KF to further optimize the SVM. With the KF, it is possible to compute the inner product directly in the HD space without the need to explicitly perform HD mapping. This allows the SVM to handle nonlinearly differentiable data with the expression shown in Eq. (7).

$$L' = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{7}$$

In Eq. (7), $L'$ represents the OF after introducing the KF, and $K(x_i, x_j)$ represents the KF. So far, the design of ISVM is completed. The flow of ISVM-based IoT NSSA method is shown in Fig. 3.

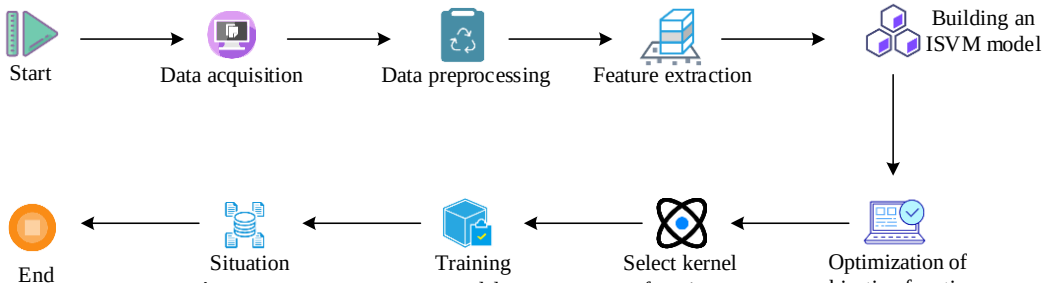



Fig. 3. Process of IoT NSSA method based on ISVM.

### B. GA-IGWO-Based Optimization of ISVM Parameters

Even though the suggested NSSA approach for ISVM exhibits great application potential when handling nonlinearly differentiable data, the KF selection and parameter setting have a significant impact on SVM performance. Its selection of parameters and penalty factors for the KF remains challenging. The model may become overfit or underfit as a result of improper parameter selection, which could impair the model's capacity for generalization and classification [18]. Therefore, the study is conducted to optimize the selection of grey wolf (GW) populations through the GWO algorithm for parameter optimization and the introduction of circular chaotic mapping instead of random generation. Meanwhile, GA is introduced to improve the optimized GWO algorithm, and a GA-IGWO-based ISVM parameter optimization method is designed. Fig. 4 displays the schematic diagram of GW hunting activity.

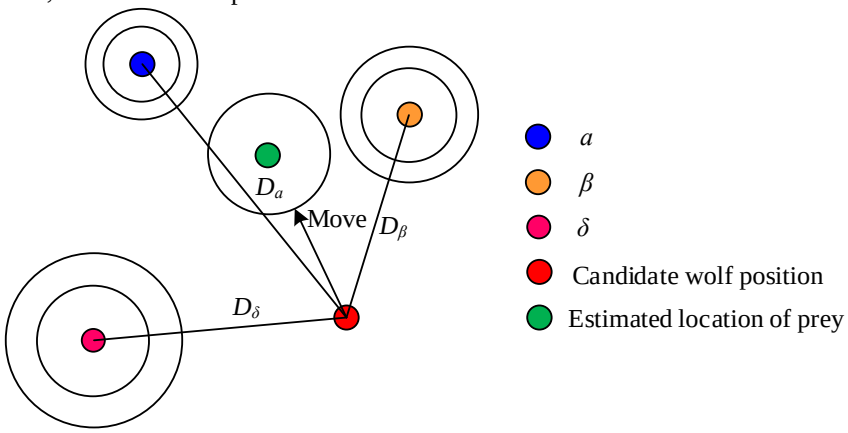



Fig. 4. Schematic diagram of GW hunting behavior.

In Fig. 4, there is a strict hierarchy in the GW group. Among them, α wolf represents the leader in the group, responsible for leading the hunt, corresponding to the optimal solution in the algorithm. The β-wolf is the secondary leader and assists the α-wolf, corresponding to the suboptimal solution. δ wolves are ordinary members that carry out the orders of α and β wolves, corresponding to the third best solution. ω wolves are ordinary members of the pack and follow other wolves in hunting. The GWO algorithm consists of three main hunting behaviors. One is stalking, chasing, and approaching prey, in which the GW searches by dispersing and then focuses on attacking the prey. The second strategy is to harass, encircle, and chase the prey until they cease moving. Attacking the victim while it stops moving is the third tactic [19]. To model the GW's prey encirclement behavior, the expression is calculated as shown in Eq. (8).

$$\begin{cases} D = | C \cdot X_p(t) - X(t) | \\ X(t+1) = X_p(t) - A \cdot D \end{cases} \tag{8}$$

In Eq. (8), $D$ is the relative distance between the current wolf and the target wolf. $A$ and $C$ are the coefficients. $X_p$ is the position of the prey. $t$ is the current iteration quantity. $X(t)$ is the position of the individual GW in the $t$ th generation. Among them, the coefficients $A$ and C are calculated as shown in Eq. (9).

$$\begin{cases} A = 2a \cdot r_1 - a \\ C = 2 \cdot r_2 \end{cases} \tag{9}$$

In Eq. (9), $r_1$ and $r_2$ represent random numbers in the interval [0, 1]. $a$ represents the convergence factor. To simulate approaching prey, $A$ is a random number in the interval [ $-a$ , $a$ ]. Over the course of the iteration, the convergence factor drops from 2 to 0. GWs have the ability to recognize the location of prey and round up the prey. Roundups are usually directed by α wolves. β-wolves and δ-wolves also occasionally participate in the hunt [20]. Eq. (10) depicts the mathematical model of a single GW locating the location of prey.

$$\begin{cases} D_\alpha = \left| -X + C_1 \times X_\alpha \right| \\ D_\beta = \left| -X + C_2 \times X_\beta \right| \\ D_\delta = \left| -X + C_3 \times X_\delta \right| \end{cases} \tag{10}$$

In Eq. (10), $D_\alpha$ , $D_\beta$ , and $D_\delta$ display the distance between $\alpha$ -wolf, $\beta$ -wolf, and $\delta$ -wolf and other individuals. $X_\alpha$ , $X_\beta$ , and $X_\delta$ display the current position of $\alpha$ wolf, $\beta$ wolf, and $\delta$ wolf, respectively. $C_1$ , $C_2$ , and $C_3$ display random numbers. Subsequently, the adjusted position of the GW can be obtained, which is calculated as shown in Eq. (11).

$$\begin{cases} X_1 = X_\alpha - A_1 \times D_\alpha \\ X_2 = X_\beta - A_2 \times D_\beta \\ X_3 = X_\delta - A_3 \times D_\delta \end{cases} \tag{11}$$

Since in the GWO algorithm, the convergence factor is the variable that mainly affects the breadth and depth search. When it is greater than 1, the GW group will expand the encirclement circle, at this time, the algorithm is mainly breadth search. When it is less than 1, the GW group will narrow the encirclement circle to complete the encirclement attack on the prey. At this time, the algorithm is mainly for the depth search. When the proportion of breadth search in the whole search process is too small, the algorithm will easily fall into the local optimum, and can not find the global optimum point. However, when the proportion of breadth search is too much, it will bring more randomness and uncertainty to the algorithm's optimization process. Therefore, the study introduces circular chaotic mapping to optimize the convergence factor, which is calculated as shown in Eq. (12).

$$\begin{cases} x_{i+1} = \left\{ x_i + r - \dfrac{\sin(2\pi x_i)}{4\pi} \right\} \bmod(1) \\ a' = 2\left(1 - \left(\dfrac{t}{t_{\max}}\right)^e\right) \end{cases} \tag{12}$$

In Eq. (12), $r$ represents the constant term, $\bmod$ represents the summation, and $a'$ represents the improved convergence factor. The flow of the IGWO is shown in Fig. 5.

In the meantime, the study presents GA to optimize the subgeneration population of the GWO algorithm because of its sluggish convergence and susceptibility to local optimization issues. It is necessary to first determine the fitness value (FF) of the $j$ th individual for each member of the GWO subgeneration population. Eq. (13) is used to determine the likelihood that a person will be chosen in a selection.

$$P_j = \frac{F_j}{\sum_{j=1}^{m} F_j} \tag{13}$$

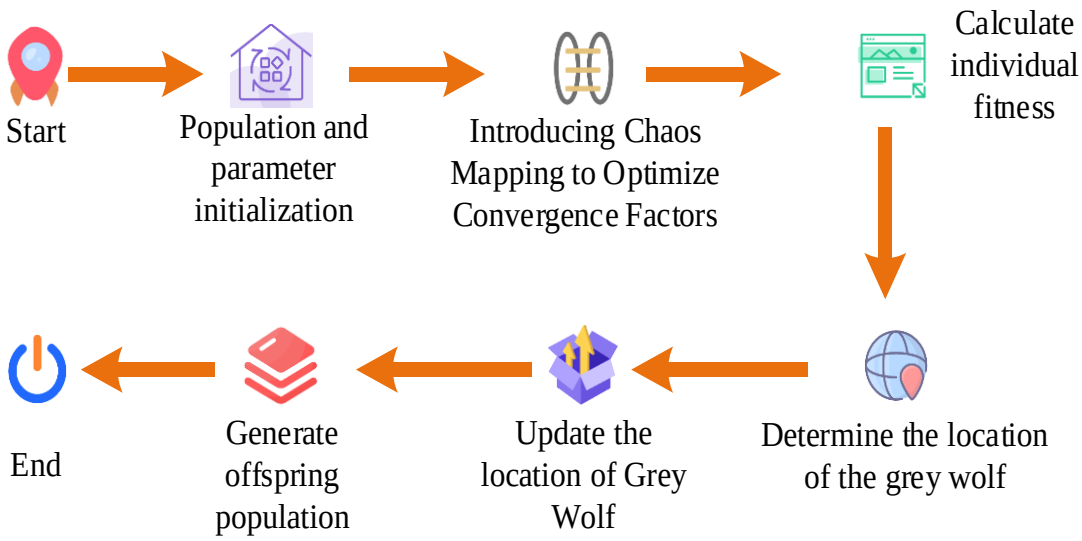



Fig. 5. IGWO process.

In Eq. (13), $P_j$ represents the probability that individual $j$ is selected in a selection. $F_j$ is the FF of the $j$ th individual. Subsequently, a crossover operation is performed to select a cut point in the chromosome. Then, one part of it is exchanged with the corresponding part of the other chromosome to obtain two new individuals. The new individual expression is shown in Eq. (14).

$$\begin{cases} x_{1j}(t)=\frac{1}{2}\times\left[(1-\gamma_j)x_{2j}(t)+(1+\gamma_j)x_{1j}(t)\right] \\ x_{2j}(t)=\frac{1}{2}\times\left[(1+\gamma_j)x_{2j}(t)+(1-\gamma_j)x_{1j}(t)\right] \end{cases} \quad (14)$$

In Eq. (14), $x_{1j}(t)$ and $x_{2j}(t)$ represent the offspring generated from a pair of parents and the crossover operator. The next step is the mutation operation, which creates a new individual by substituting different alleles for gene values at specific loci in the coding strings of the individual chromosomes. For each locus $g_j$, the range of continuous uniform distribution of the mutation is determined with the mutation probability. A random perturbation is added to its value to generate a new individual. The calculation is shown in Eq. (15).

$$g'_j = g_j + \delta \quad (15)$$

In Eq. (15), $g'_j$ represents the mutated locus. $\delta$ represents the random perturbation drawn from the uniform distribution. Finally, the mean absolute percentage error (MAPE) is used to construct the FF to calculate the FF and the optimal parameters. The FF is shown in Eq. (16).

$$f(y)=\frac{1}{1+MAPE(y)} \quad (16)$$

In Eq. (15), $y$ represents the optimal parameters and $MAPE$ represents MAPE. The flow of GA-IGWO is shown in Fig. 6.

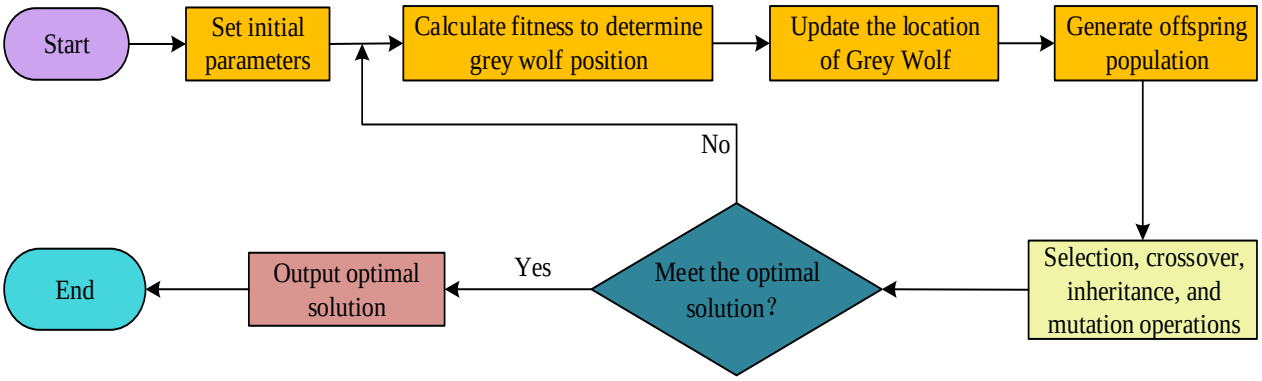



Fig. 6. GA-IGWO flow.

## IV. Effectiveness Analysis of ISVM-GA-IGWO-Based IoT NSSA Algorithm

This section deals with the effectiveness analysis of ISVM-GA-IGWO-based IoT NSSA algorithm. The first section shows the performance analysis results of ISVM-GA-IGWO based IoT NSSA algorithm. The second section shows the results of practical application effect of ISVM-GA-IGWO NSSA algorithm.

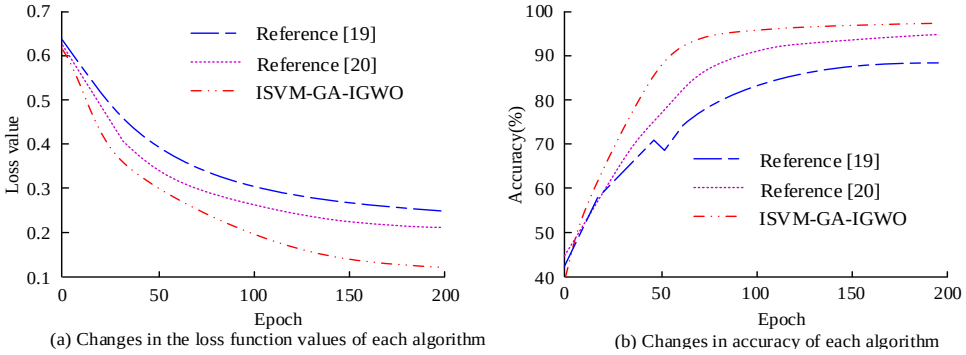
### A. Performance Analysis of ISVM-GA-IGWO NSSA Algorithm

To validate the performance of ISVM-GA-GWO-based IoT NSSA algorithm, the study is carried out on an operating system equipped with Intel core i7-11390H central processor, 32 GB of running memory, 32 GB of video card memory and Windows 11. The simulation is also analyzed using Python 3.7. The maximum iteration of the ISVM-GA-GWO algorithm is firstly set to 200, the population size is set to 50, the crossover operator is 0.7, and the variation operator is 0.02. The accuracy of ISVM-GA-GWO is firstly verified by introducing mean absolute error (MAE), root mean square error (RMSE), and MAPE. It is also compared with SVM, and GWO, methods in [19] and [20]. Table I displays the findings.

TABLE I Training Parameters of the Model

| Model | MSE | RMSE | MAPE |
|---|---|---|---|
| SVM | 0.0213 | 0.125 | 0.0032 |
| GWO | 0.0142 | 0.114 | 0.0053 |
| Reference [19] | 0.0112 | 0.092 | 0.0026 |
| Reference [20] | 0.0089 | 0.074 | 0.0021 |
| ISVM-GA-IGWO | 0.0064 | 0.041 | 0.0013 |

In Table I, the MAE, RMSE, and MAPE of ISVM-GA-IGWO are 0.0064, 0.041, and 0.0013, respectively. The MSEs of [20], [19], GWO, and SVM are 0.0089, 0.0112, 0.0142, and 0.0213, respectively. Their RMSE is 0.074, 0.092, 0.114, 0.125, and MAPE is 0.0021, 0.0026, 0.0053, 0.0032, respectively. It can be found that the values of the three indexes of ISVM-GA-IGWO are significantly lower than those of other algorithms, which proves that it is more accurate. To further verify the accuracy of ISVM-GA-IGWO, the study calculates the loss and accuracy of different models separately and compares them with other algorithms. The results are shown in Fig. 7.




(a) Changes in the loss function values of each algorithm (b) Changes in accuracy of each algorithm

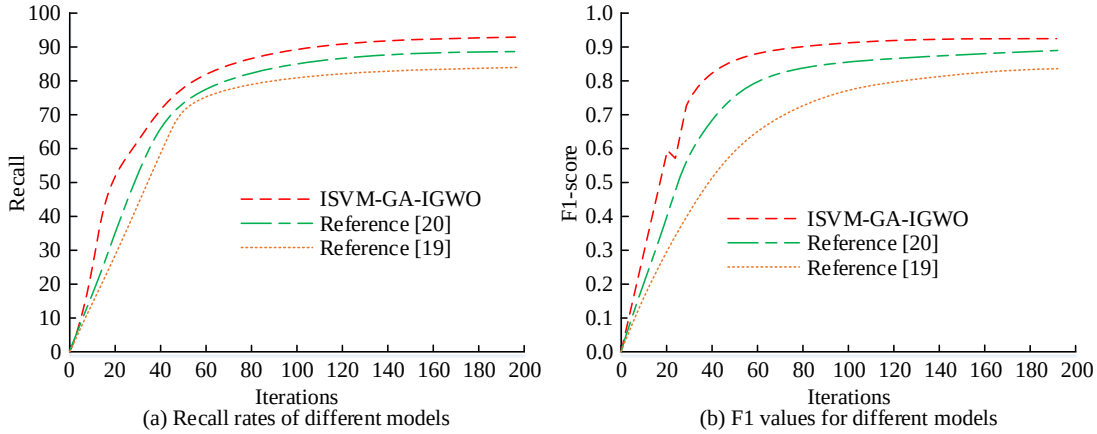
Fig. 7. Value of loss function and accuracy of each algorithm.

In Fig. 7(a), the loss of the algorithm in [19] is 0.25, the loss of the algorithm in [20] is 0.21, and the loss of the proposed ISVM-GA-IGWO is 0.13. The three algorithms have corresponding accuracy rates of 89.2%, 95.6%, and 98.1% in Fig. 7(b). Its superior accuracy is further demonstrated by the fact that ISVM-GA-IGWO has a smaller loss and a greater accuracy rate than the other two algorithms. To provide further validation of the performance of the proposed IoT network security situation assessment algorithm based on ISVM-GA-GWO, five indicators, including area under curve (AUC), memory usage, throughput, average detection time, and false alarm rate, are introduced to calculate the non-algorithmic indicator values. The comparison results are shown in Table II.

In Table II, the AUC, memory usage, throughput, average detection time, and false positive rate of the SVM algorithm are 0.855, 483 MB, 74.8 Mbps, 5.1 s, and 14.6%, respectively. The five indicators of GWO are 0.887, 412 MB, 78.5 Mbps, 4.3 s, and 11.2%, respectively. The five indicator values of SVM-GA-GWO are 0.923, 356 MB, 82.1 Mbps, 3.8 s, and 9.1%, respectively. The five indicator values of the algorithm in [19] are 0.946, 328 MB, 85.6 Mbps, 3.5 s, and 8.5%, respectively. The five indicator values of the algorithm in [20] are 0.952, 289 MB, 91.2 Mbps, 2.7 s, and 5.3%, respectively. The five indicators of the ISVM-GA-IGWO algorithm are 0.981, 224 MB, 97.3 Mbps, 1.2 s, and 2.2%, respectively. It can be observed that compared to other algorithms, the proposed ISVM-GA-IGWO algorithm has significantly higher AUC values and throughput, with a maximum AUC increase of 0.126 and a maximum throughput increase of 22.5 MB. However, a marked decline in memory usage, average detection time, and false alarm rate has been observed. Specifically, the memory usage can be reduced by up to 259 Mbps, the average detection time can be reduced by up to 3.9 s, and the false alarm rate can be reduced by up to 12.4%. The aforementioned results demonstrate that the proposed IoT network security situation assessment algorithm based on ISVM-GA-GWO performs well in terms of detection accuracy, real-time performance, and resource utilization. Lastly, the algorithm in [20], ISVM-GA-IGWO, and the algorithm in [19] are evaluated for recall and F1 value. Fig. 8 displays the findings.

TABLE II COMPARISON OF INDICATOR VALUES FOR DIFFERENT ALGORITHMS

| Model | AUC | Memory usage (MB) | Throughput (Mbps) | Mean time to detect (s) | False alarm rate (%) |
|---|---|---|---|---|---|
| SVM | 0.855 | 483 | 74.8 | 5.1 | 14.6 |
| GWO | 0.887 | 412 | 78.5 | 4.3 | 11.2 |
| SVM-GA-GWO | 0.923 | 356 | 82.1 | 3.8 | 9.1 |
| Reference [19] | 0.946 | 328 | 85.6 | 3.5 | 8.5 |
| Reference [20] | 0.952 | 289 | 91.2 | 2.7 | 5.3 |
| ISVM-GA-IGWO | 0.981 | 224 | 97.3 | 1.2 | 2.2 |




(a) Recall rates of different models (b) F1 values for different models

Fig. 8. Recall rates and F1 values of different models.

Fig. 8(a) illustrates the recall of the three algorithms. The recall of ISVM-GA-IGWO is 93.7%, the recall of the model in [20] is 89.3%, and the recall of the model in [19] is 83.6%. Fig. 8(b) demonstrates the F1 value of the three algorithms. The F1 value of the three algorithms is 0.94, 0.90, and 0.84, respectively. The suggested ISVM-GA-IGWO method provides a recall rate that is 4.4% and 10.1% greater than the algorithms in [19] and [20], and its F1 value is 0.04 and 0.10 higher than those of the other two algorithms, respectively. It shows that ISVM-GA-IGWO has better overall performance.

### B. *Analysis of the Effect of Practical Application of ISVM-GA-IGWO NSSA Algorithm*

To verify the practical application of the designed ISVM-GA-IGWO based IoT NSSA algorithm, the study firstly validates the ISVM-GA-IGWO model in five aspects, namely, whether it supports attribute revocation, offline encryption, outsourcing decryption, authorization center, and key length. The support is denoted as T and not as F. The unit key length is denoted by L and compared with the other two algorithms. Table III displays the findings.

In Table III, for the first four aspects, ISVM-GA-IGWO performs T. The ABE algorithm performs T in three aspects: attribute revocation, offline encryption, and outsourcing decryption. It performs F in authorization centers. The FHE algorithm performs the same way as the ABE algorithm in the four aspects. The key length L+1 of ISVM-GA-IGWO is smaller than ABE algorithm and FHE algorithm. The above outcomes indicate that the ISVM-GA-IGWO is more powerful. The next step is to calculate the data access control effect of different algorithms within 600 ms respectively. The results are shown in Fig. 9.

In Fig. 9, when access control is performed by the ISVM-GA-IGWO, the predicted curves largely coincide with the actual curves. When access control is performed using the FHE algorithm, the predicted curves deviate significantly from the actual curves around 120 ms and 480 ms. It indicates that the ISVM-GA-IGWO fitting performance is better and works better in practical applications. Next, the overhead and time during communication is calculated and the results are compared with other algorithms as shown in Fig. 10.

TABLE III FUNCTIONAL COMPARISON OF DIFFERENT ALGORITHMS

| Algorithm | ABE | FHE | ISVM-GA-IGWO |
|---|---|---|---|
| Access structure | F | F | T |
| Offline encryption | F | F | T |
| Outsourced encryption | F | F | T |
| Authority center | T | T | T |
| Key length | 2L+4 | 2L+1 | L+1 |

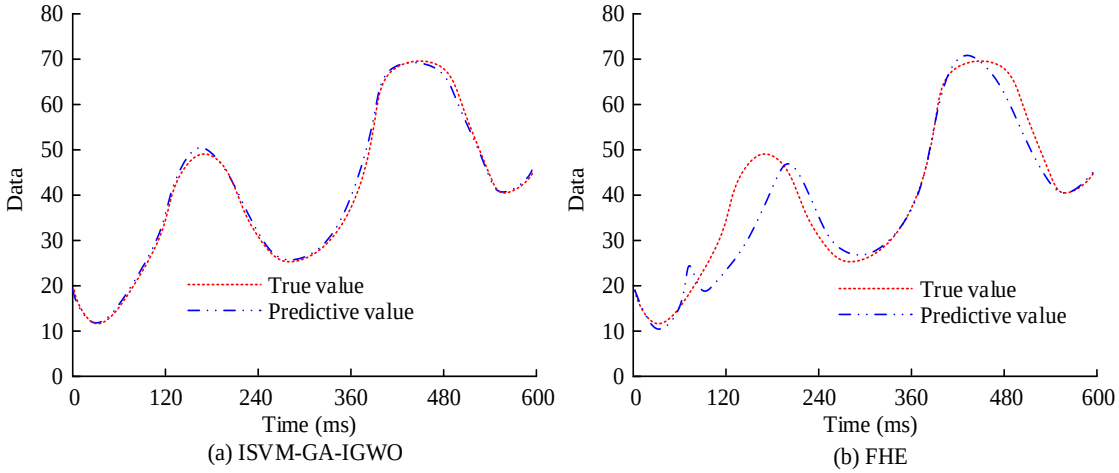



Fig. 9. Data processing capacity of different algorithms within 1000 ms.

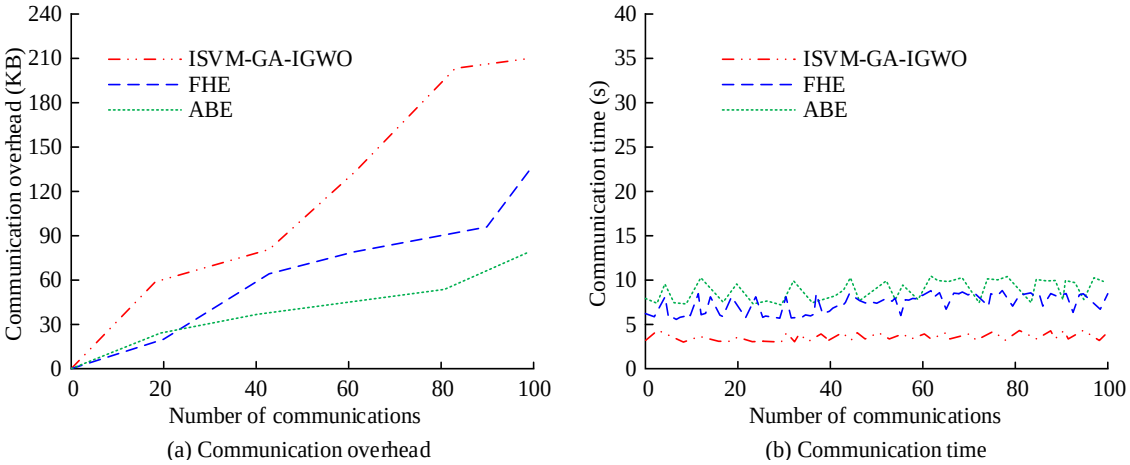



Fig. 10. Communication overhead between different decryption algorithms is sent to data centers and sent to data receivers.

In Fig. 10(a), the communication overheads of the different algorithms all show an increasing trend as the communication increases. When the communication reaches 100 times, the communication overhead of ISVM-GA-IGWO is 81.3 KB, which is significantly lower than 134.6 KB of FHE algorithm and 211.5 KB of ABE algorithm. In Fig. 10(b), the average communication time of ABE algorithm, FHE algorithm, and ISVM-GA-IGWO is 8.11 s, 6.37 s, and 3.59 s. The average communication time of ISVM-GA-IGWO is significantly lower than the other methods. The above outcomes display that the ISVM-GA-IGWO can effectively reduce the communication cost and delay, which further proves that its practical application is more effective. To verify the effectiveness of the proposed ISVM-GA-IGWO network security situation assessment algorithm in practical applications, the proposed method is validated in several scenarios. These scenarios include an intelligent furniture network containing 50 smart devices, an industrial control system based on Modbus protocol, intelligent urban traffic monitoring deployed on traffic signal lights and camera networks, a medical IoT with electrocardiogram monitors and insulin pump devices, and a vehicle-to-infrastructure communication simulation. The results are shown in Table IV.

TABLE IV EVALUATION RESULTS OF ISVM-GA-IGWO ALGORITHM IN DIFFERENT SCENARIOS

| Test scenario | Anomaly detection rate (%) | False positive rate (%) | Average response time (s) | Communication overhead (KB) |
|---|---|---|---|---|
| Smart home network | 96.2 | 1.3 | 5.8 | 82.1 |
| Industrial control system | 94.8 | 0.9 | 7.2 | 85.7 |
| Smart city traffic monitoring | 97.5 | 1.1 | 6.4 | 78.9 |
| Medical Internet of Things | 95.1 | 0.7 | 8.1 | 90.3 |
| Internet of Vehicles | 93.6 | 1.5 | 9.5 | 102.5 |

As illustrated in Table IV, the proposed ISVM-GA-IGWO network security situation assessment algorithm demonstrates a noteworthy performance in terms of anomaly detection, with a rate of 96.2%. The algorithm exhibits a low false alarm rate of 1.3%, an average response time of 5.8 seconds, and a communication overhead of 82.1 KB. In industrial control systems, smart city traffic monitoring, medical IoT, and vehicle networking, the proposed algorithms have anomaly detection rates of 94.8%, 97.5%, 95.1%, and 93.6%, and false alarm rates of 0.9%, 1.1%, 0.7%, and 1.5%, respectively. The average response times are 7.2 s, 6.4 s, 8.1 s, and 9.5 s, respectively, and the communication overheads are 85.7 KB, 78.9 KB, 90.3 KB, and 102.5 KB, respectively. It has been demonstrated that, under various conditions, the algorithm exhibits a high capability for anomaly detection and a low rate of false alarms, while maintaining minimal response time and communication overhead. These observations suggest that the proposed ISVM-GA-IGWO network security situation assessment algorithm is well-suited to meet the stringent requirements of precision and real-time performance in practical scenarios.

## V. Discussion

The research aimed to solve the problem of poor performance of traditional IoT network performance analysis methods in handling random nonlinear features, and proposed a network security situation assessment method based on ISVM-GA-IGWO. The MAE value of this method was 0.0064, the RMSE value was 0.041, and the MAPE value was 0.0013, which were significantly lower than other algorithms, indicating its high prediction accuracy. This was similar to the conclusion of Thota S et al [15]. In contrast, ISVM-GA-IGWO was significantly better because the GA-IGWO optimization resulted in better parameters, allowing the model to better fit complex data. The F1 value of the ISVM-GA-IGWO algorithm was 0.94, with a recall rate of 93.7%, indicating its good overall performance. This was consistent with the conclusion drawn by Oseni et al. [6], but the ISVM-GA-IGWO algorithm performed better. This was because the proposed algorithm introduced GWO and optimized it by circular chaotic mapping. At the same time, it introduced radial basis KFs to perform kernel mapping on FVs, which significantly improved the performance. The memory usage of the ISVM-GA-IGWO algorithm was only 224 MB, which proved its good resource utilization. This result was similar to the conclusion of Shi G [14]. Compared with these two methods, the proposed method was obviously better. Because, in the optimization process of ISVM-GA-IGWO algorithm, the method avoided redundant parameter storage and complex computation process by reasonably setting the population size, optimizing the genetic operation, and simplifying the design of ISVM model, which effectively reduced the memory overhead. In summary, the ISVM-GA-IGWO algorithm proposed in this study demonstrates significant advantages in the field of IoT network security situation assessment, providing technical support for the application of IoT in more complex scenarios.

## VI. Conclusion

With the surge in the number of IoT devices, the complexity and uncertainty of network traffic have increased significantly, and the cyber security threats have become increasingly severe. Traditional cyber security detection methods, such as rule-based and statistical approaches, have been difficult to cope with the nonlinearly differentiable data and dynamically changing network environment in the IoT environment. The research aimed to address the shortcomings of traditional methods in dealing with nonlinearly differentiable data and to improve the robustness of the model in the face of new attack types and unknown data. It proposed an ISVM-based IoT NSSA method and optimized the parameters of ISVM by combining GA and IGWO. The results revealed that the MAE, RMSE, and MAPE of ISVM-GA-IGWO were 0.0064, 0.041, and 0.0013, respectively. Compared to the values of the three indexes of the four algorithms in [20], [19], GWO, and SVM, it was much lower, demonstrating its great accuracy. ISVM-GA-IGWO had a loss of 0.13 and an accuracy of 98.1%, which was lower than the other methods and higher than the other methods, further proving its higher accuracy. When access control was performed by ISVM-GA-IGWO, the predicted curve basically overlapped with the actual curve. When using the FHE algorithm for access control, the prediction curves had large deviations from the actual curves around 120 ms and 480 ms, indicating that the ISVM-GA-IGWO was more effective in practical application. However, despite the introduction of GA-IGWO algorithm for parameter optimization, it may still fall into local optima in some cases, resulting in unsatisfactory optimization results. At the same time, the proposed ISVM-GA-IGWO hybrid algorithm increases the resource consumption to a certain extent, and the model performance is highly dependent on high-quality annotated data, while in actual IoT environments, abnormal samples are rare and annotation costs are high. In addition, the device state and network topology in IoT may change frequently, and the current model lacks adaptability to dynamic environments. Subsequent research endeavors will introduce more efficient parameter optimization algorithms, such as adaptive parameter control or dynamic weight adjustment, to enhance the convergence speed and robustness of the model. Meanwhile, multi-objective optimization methods will be explored to simultaneously optimize multiple performance indicators. In addition, semi- or self-supervised learning will be combined to reduce the dependence on annotated data, and online learning or incremental update mechanisms will be added to adapt to dynamic scenarios.

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# Experiential Landscape Design Using the Integration of Three-Dimensional Animation Elements and Overlay Methods

Mingjing Sun*, Ming Wei
School of Design and Art, Shandong Huayu University of Technology, Dezhou 253011, China

***Abstract*—This work aims to optimize users' immersive experiences, enhance design effectiveness, and construct a scientific evaluation system for landscape design. The work begins with the collection and analysis of spatial data from the landscape design area, using 3D animation technology to generate visual models and virtually reconstruct key landscape elements. Next, the overlay method is applied to visually stratify elements within the space, progressively building a multi-layered, logical spatial structure to enhance realism and information communication efficiency in landscape design. To evaluate design effectiveness, a user experience questionnaire and behavior tracking experiments are designed. The questionnaire covers three dimensions: immersion, satisfaction, and interactivity, while the behavioral tracking experiment collects data on user dwell time and gaze movement in virtual scenes. Results indicate that the design scheme based on 3D animation and layering significantly outperforms traditional designs in terms of immersive experience, clarity of structure, and user engagement. In the questionnaire, the average satisfaction rating for the design scheme is 4.7 (out of 5), with an immersion rating average of 4.8. The behavioral tracking experiment shows a 40% increase in dwell time compared to traditional designs, and users' willingness to revisit improves by 26% compared to the control group. This work innovatively applies 3D animation and overlay methods to experiential landscape design, confirming the practical value of this method in optimizing user experience and design effectiveness.**

***Keywords*—*3D animation integration; overlay method; experiential landscape design; user immersive experience; evaluation system design***

## I. Introduction

In recent years, with the rapid development of three-dimensional (3D) animation technology and Virtual Reality (VR) technology, experiential design has become an important trend in the field of landscape design [1]. Traditional landscape design mainly relies on two-dimensional drawings and physical models. However, these methods are difficult to meet the modern needs of users for a sense of realism and immersion. For example, static models cannot dynamically present seasonal changes or real-time interactions, and this results in limited user engagement [2, 3]. Modern users increasingly expect experiential design to provide an immersive interactive experience, transforming landscape design from mere static viewing into dynamic participation. This demand has promoted the application of 3D animation technology in landscape design, allowing for the visualization and virtual reconstruction of landscape spaces. Moreover, it enables designs that go beyond the limitations of two-dimensional images or simulated effects to dynamically simulate real spatial environments. For example, Balcerak Jackson et al. (2024) analyzed the correlation between VR and immersive experiences from a philosophical perspective, and emphasized the impact of dynamic interaction on users' perception [4]; Park et al. (2020) proposed a landscape design methodology based on users' memory schemas and enhanced the continuity of the user experience through a dynamic feedback mechanism [5]; Kim et al. (2021) explored the potential of 3D printing technology in landscape design. By combining physical models with virtual dynamic effects, they broke through the limitations of two-dimensional images and achieved the dynamic simulation of real spatial environments [6]. Meanwhile, the application of overlay methods in spatial design has also garnered increasing attention. Through 3D animation technology, the dynamic effects of landscape elements (such as vegetation and water bodies) are accurately simulated. For example, SpeedTree is used to generate high-precision tree models, and the fluid simulator of Blender is combined to achieve dynamic changes in water flow. The overlay method constructs a multi-level logical structure by layering and superimposing spatial data (such as terrain, vegetation layers, and hydrological layers) to enhance the visual depth. For instance, Chen (2024) stratified and superimposed terrain and architectural elements through 3D VR technology, and verified the effect of the multi-level logical structure on enhancing visual depth [7]; Xing and Puntien (2024) proposed a hierarchical reconstruction strategy for the landscape of abandoned mining areas from the perspective of naturalistic aesthetics. They used the overlay method to coordinate ecological restoration and visual logic [8]; Qin (2022) combined the particle swarm optimization algorithm and proposed an overlay mapping design framework for intelligent rural landscapes. This framework achieves accurate stratification of complex elements through dynamic parameter adjustment [9]. These studies indicate that the combination of 3D animation technology and the overlay method can achieve richer and more realistic visual effects through virtual reconstruction and hierarchical logic. Meanwhile, it can provide multi-dimensional support for user interaction. Therefore, finding effective ways to integrate 3D animation technology with overlay methods to optimize user experience and build a scientific evaluation system for experiential landscape design has become a pressing issue that needs to be addressed.

The primary objective of this work is to propose a novel experiential landscape design method based on the integration

of 3D animation elements and overlay methods, thus effectively enhancing users' immersive experiences and optimizing design outcomes. The work focuses on how to organically combine virtual and real elements using 3D animation technology and overlay methods to create designs that possess depth and visual richness. This work intends to achieve significant results in visual communication, information presentation, and user interaction [10]. Additionally, a systematic evaluation method for experiential landscape design is proposed, which quantitatively measures users' immersion, interactivity, and satisfaction to scientifically assess the effectiveness of the design schemes. User data are collected through experience questionnaires and behavioral tracking experiments in virtual scenes. Through these data, the work aims to evaluate the real-world performance of the design solutions, providing a scientific basis for the assessment of experiential landscape design. Moreover, this work seeks to reveal the practical value and applicability of combining 3D animation technology with overlay methods in landscape design through data analysis. It aims to refine the theoretical framework of experiential design and offer more actionable guidance for future VR applications in landscape design.

This work holds significant importance on both theoretical and practical levels. First, from a theoretical perspective, it introduces 3D animation technology and overlay methods into experiential landscape design, providing a new viewpoint for innovation in landscape design methodologies. Currently, there is a lack of systematic methodological research on experiential design in the landscape architecture field, particularly regarding the integration of virtual elements with real environments. The combination of 3D animation and overlay methods addresses existing deficiencies in design methods. By employing multi-layered spatial division through overlay methods and virtual reconstruction with 3D animation technology, this work enriches the theoretical foundations of experiential design. Moreover, it offers innovative ideas for future studies on how to integrate 3D animation and overlay methods into landscape design. Additionally, on a practical level, the proposed design methods and evaluation systems provide direct guidance for the application of landscape design. Experiential landscape design has broad demand in industries such as commerce and tourism, and it is gradually being promoted in areas like public facilities and cultural heritage preservation. This study validates the effectiveness of the design through behavioral tracking experiments and questionnaire data, providing scientific support for user experience enhancements. This establishes feasible optimization pathways for future experiential landscape design. The application potential of this method is not limited to landscape design. For example, in urban planning, 3D animation and the overlay method can simulate the changes in traffic flow and building shadows. This can assist decision-makers in evaluating the feasibility of plans. In game design, the dynamic layering technology can create a more realistic open world, and the AI-driven interaction mechanism can enhance the players' sense of immersion. Future research will further explore the possibilities of cross-disciplinary integration.

This work is divided into six sections, and the research is carried out systematically. Section I is the introduction. It provides an overview of the research background of 3D animation technology and the overlay method in landscape design. It points out the deficiencies of existing methods in terms of technical integration and quantitative evaluation of user experience, and puts forward the research objectives and innovative points of this work. Section II is the literature review. It systematically combs through the relevant research on 3D animation, the overlay method, and user experience evaluation in the field of landscape design. Moreover, it clarifies the limitations of existing work, and defines the breakthrough direction of this work. Section III is the method design. It elaborates in detail on the technical framework that integrates the dynamic simulation of 3D animation and the layering logic of the overlay method. It includes the specific implementation processes of virtual reconstruction, layering and superposition, and the interaction feedback mechanism. Section IV is the experiment and result analysis. Through the cross-scenario comparative experiments, long-term user tracking, and eye movement data collection, the sense of immersion, interactivity, and user satisfaction of the design scheme are quantitatively evaluated. Besides, the key data are presented in the form of numerical tables. Section V is the discussion. Based on similar methods in the literature, it deeply analyzes the technical advantages and limitations of the scheme proposed, and explores its expansion potential in fields such as urban planning and cultural heritage protection. Section VI is the conclusion. It summarizes the research results and proposes the directions for future improvement. Through the above structure, this work aims to provide a complete methodology for experiential landscape design that combines theoretical innovation and practical guidance.

## II. Literature Review

In the field of experiential landscape design, the applications of 3D animation technology and overlay methods have gradually attracted the attention of scholars. In recent years, with advancements in technology, researchers have conducted in-depth explorations on how to enhance user immersion and interactivity. Hussein et al. (2023) studied the application of VR technology in landscape design, emphasizing that VR could provide users with an immersive experience [11]. Their research indicated that by creating interactive virtual environments, users could more intuitively understand the spatial characteristics of landscape design, thereby enhancing design effectiveness. However, their research primarily focused on the application of VR technology and provided relatively little discussion on specific design methods. Meanwhile, Zou et al. (2022) provided a detailed analysis of the application of overlay methods in spatial design, noting that layering could effectively enhance the logic and visual depth of spaces [12]. By stratifying and reconstructing different visual elements, layering not only improves the aesthetic effect of spatial design but also enhances users' spatial cognition. However, their research did not combine overlay methods with modern 3D animation technology, nor did it explore the improvements in user experience resulting from their integration, highlighting a direction for future research. Additionally, Hao et al. (2020) found that user initiative during the design process significantly affected satisfaction in interactive landscape design [13]. Their research demonstrated that enhancing user participation could markedly improve the effectiveness of design solutions. However, they did not

specifically analyze how to achieve user participation and interaction through technological means, underscoring the importance of technical integration here. Furthermore, Dirin et al. (2023) studied the sense of immersion in experiential design, suggesting that immersion was a key factor influencing user satisfaction [14]. They quantified user immersion and validated the positive correlation between immersion and satisfaction. However, they did not delve into how to specifically enhance immersion through design methods, providing theoretical support for the current research. In another study, Saorin et al. (2023) analyzed the importance of user behavior in experiential landscape design. They collected activity data from users in virtual scenes through behavioral tracking experiments and found a significant correlation between users' dwell time and design effectiveness [15]. However, their research mainly focused on analyzing user behavior, lacking a comprehensive assessment of design solutions. This suggests that this work should combine user behavior analysis with design effectiveness evaluation. Lastly, Shen et al. (2024) compared the effects of traditional design methods and emerging technologies in landscape design, finding that the latter offered significant advantages in user experience [16]. They emphasized the crucial role of digital technology in enhancing design effectiveness but lacked a systematic exploration of specific technological combinations. Therefore, this work delves into the integration of 3D animation and overlay methods to fill this gap.

Zhang et al. (2022) investigated the application of multimedia technology in public landscape design, emphasizing that interactivity and participation were key factors influencing user experience [17]. They proposed enhancing the user experience through various media approaches. However, their research provided limited details on technical implementation and did not offer practical solutions. This is an aspect this work aims to explore in depth. Li et al. (2023) noted in their study on digital finance and corporate financing constraints that the application of digital technology could effectively improve the efficiency of resource allocation within companies [18]. This insight is relevant to the optimization of 3D animation technology in landscape design discussed here.

In summary, while numerous studies have focused on 3D animation technology, overlay methods, and user experience in the realm of experiential landscape design, there are still significant shortcomings. Most research rarely combines 3D animation with overlay methods to achieve a deeper enhancement of user experience. Furthermore, there is a relative lack of exploration regarding the establishment of a quantitative evaluation system for design effectiveness. Additionally, many studies concentrate primarily on theoretical discussions and user behavior analysis, lacking specific technical application examples and failing to form a systematic, actionable design framework. Therefore, the innovation of this work lies in the organic integration of 3D animation technology and overlay methods to construct a systematic experiential landscape design method aimed at enhancing user immersion and participation. Simultaneously, by utilizing user experience questionnaires and behavioral tracking experiments, this work establishes a scientific evaluation system, providing theoretical and practical support for future studies and filling the existing gaps in the literature.

## III. METHODS

### A. Virtual Reconstruction and Integration of 3D Animation Technology in Landscape Design

One of the core applications of 3D animation technology in landscape design is the virtual reconstruction and integration of key landscape elements. By dynamically simulating scenes such as vegetation, water bodies, terrain, and buildings, 3D animation not only showcases static visual elements but also mimics their changes under different temporal or environmental conditions. This enhances the overall expressive quality of the design [19, 20]. In natural landscape design, the dynamic growth of plants and seasonal changes are crucial components of the ecosystem. This work utilizes 3D modeling software (SpeedTree) to generate highly realistic models of trees, shrubs, and herbaceous plants, and incorporates animation techniques to simulate the dynamic effects of wind, seasonal transitions, and growth cycles [21, 22]. These simulations not only enhance the realism of the landscape but also provide users with a dynamic experience of perceiving the passage of time and seasonal changes. Water bodies are indispensable elements in landscape design, and their dynamic forms—such as flowing water, ripples, and reflections—significantly influence the visual atmosphere of the entire space. This work employs 3D animation technology for detailed modeling and dynamic simulation of water features, including rivers, lakes, and fountains. Building on this foundation, fluid dynamics-based animation algorithms (Blender's fluid simulator) are utilized to achieve real-time changes in water dynamics, encompassing flow speed, direction, and wave effects.

To enhance the realism of landscape design, this work incorporates dynamic simulations of weather and lighting effects. By adjusting light sources, shadows, and atmospheric scattering effects, it simulates landscape changes at various time of day (daytime, dusk, and nighttime) and different weather conditions (sunny, rainy, and snowy). For example, on sunny days, strong shadows are cast by sunlight, while on rainy days, water droplets collect on roofs and surfaces, accompanied by wet material effects.

In addition to virtual reconstruction, another important application of 3D animation technology is to enhance interactivity between users and landscape designs. In experiential landscape design, by introducing interactive features, users can not only "view" the landscape but also actively participate, making interactive decisions and seeing real-time impacts of their actions on the environment. This work primarily utilizes sensors, motion capture devices, and VR equipment (such as VR headsets and Leap Motion gesture controllers) to achieve this interactive design. In the virtual environment, users can interact with elements in the 3D landscape through gestures, eye movements, and other means [23, 24]. For instance, users can control the direction of water flow with hand movements or click on specific areas to view detailed information about plants. This direct form of interaction significantly enhances users' sense of participation and immersion. Fig. 1 illustrates the process of virtual reconstruction and integration of 3D animation technology in landscape design.

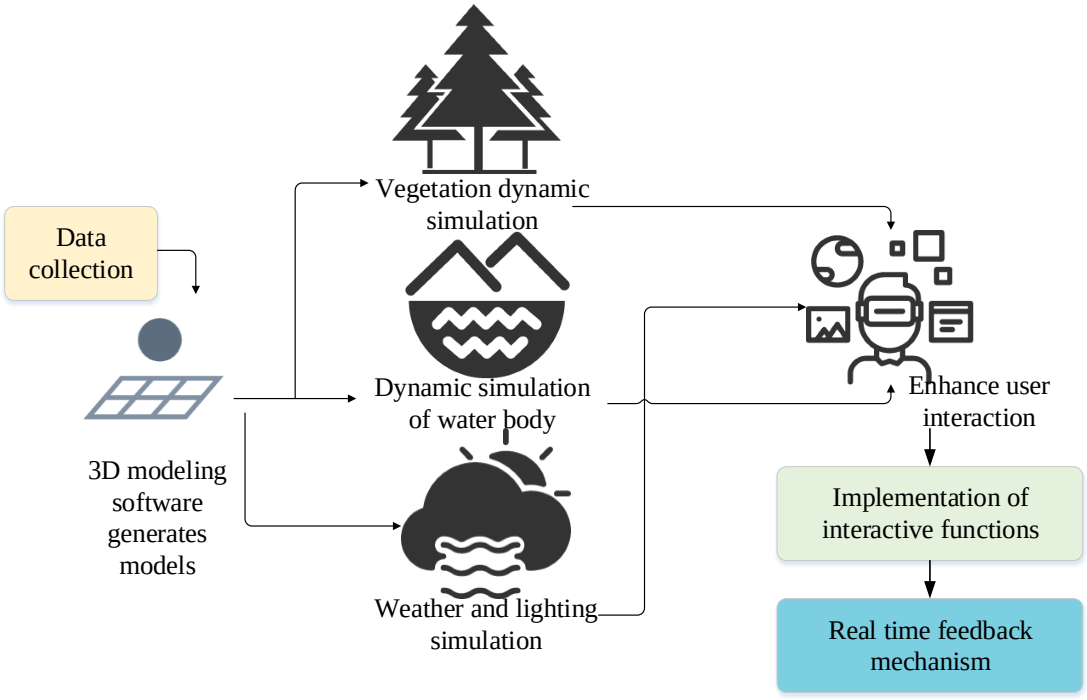


Fig. 1. The process of virtual reconstruction and integration of 3D animation technology in landscape design.

By integrating a physics simulation engine with user data tracking technology, this work has designed a real-time feedback mechanism. When users perform certain actions in the virtual environment (such as changing their viewpoint or triggering the swaying of trees), the system responds immediately based on the parameters input by the user, providing feedback through various channels such as visuals and sound. For example, as a user approaches a grove, the leaves may rustle in the wind, accompanied by a soft rustling sound. This multi-sensory feedback further enhances the immersive experience. In addition to the basic interaction functions (such as controlling the water flow with gestures and clicking to view plant information), this work further explores the user-defined environment and the AI-driven dynamic adaptation mechanism. For example, users can adjust the seasonal parameters of the virtual scene through voice commands (such as switching to the autumn mode), and the system will update the vegetation colors and weather effects in real time. Furthermore, based on user behavior data (such as the duration of stay and the trajectory of the line of sight), the AI algorithm can automatically optimize the landscape layout. If most users frequently focus on a certain area, the system will suggest adding interactive nodes or visual focal points in that area to achieve dynamic design optimization. Table I lists common forms of user interaction feedback.

TABLE I. COMMON FORMS OF USER INTERACTION FEEDBACK

| Interactive Object | Feedback Form | Expected Effect |
|---|---|---|
| Vegetation | Leaf movement, sound effects | Enhance the realism of the natural environment |
| Water | Wave dispersion, reflection adjustments | Enhance visual and auditory interactivity |
| Buildings | Shimmering, rotation | Increase user interest |

### B. *The use of the Overlay Method and Layering of Visual Elements*

The overlay method is a spatial analysis technique commonly used in Geographic Information Systems (GIS). It involves progressively stacking different spatial data layers to create a multidimensional and multi-layered composite spatial view [25, 26]. In landscape design, the overlay method effectively assists designers in organizing complex environmental elements, and optimizing visual representation and information communication. This work integrates the overlay method with 3D animation technology, leveraging its powerful layering capabilities to logically separate natural landscapes and artificial structures. It ensures that each layer's elements do not interfere with one another but instead complement each other, thereby achieving higher design accuracy and enhancing user experience. The core concept of the overlay method is to decompose a series of spatial information into multiple independent layers and overlay these layers to provide a holistic spatial view. Each layer can encompass different categories of information, such as topography, vegetation, and water features.

Here, the overlay method is used to conduct a detailed layering of the main visual elements in landscape design. This approach not only simplifies complex landscape design tasks but also enhances the sense of depth and interactivity of the elements within the virtual landscape. Fig. 2 illustrates the process of layering visual elements based on the overlay method and enhancing interactivity. Topography serves as the foundation for any landscape design; therefore, this work designates it as the first layer. Using collected Digital Elevation Model (DEM) data, the topography layer is created to simulate the actual terrain variations. This layer includes hills, plains, and low-lying areas, providing the design framework and offering important

references for subsequent building layouts and road planning. Above the topography layer, a vegetation layer is added. This layer comprises natural vegetation elements such as trees, shrubs, and grass. Based on field data and LiDAR point cloud information, the distribution, density, and types of vegetation are classified, with virtual plant models added to the corresponding locations. Additionally, 3D animation technology enables the dynamic simulation of plant growth and seasonal changes. The vegetation layer enriches the visual effects of the scene and provides essential data for ecological design. Water features are crucial elements that shape landscapes, and their dynamic characteristics (such as flowing water and the rippling of lakes) are vital for creating visual and auditory experiences. This work designates water as the third layer, including rivers, ponds, and wetlands. Through 3D animation technology, the flow of water is successfully simulated, and water levels are adjusted based on seasonal precipitation. Furthermore, the dynamic simulation of the hydrological layer reflects the physical properties of water, such as transparency, reflection, and refraction. Based on the aforementioned natural elements, building structures and roads are overlaid as the fourth layer. This layer contains all man-made structures, such as visitor centers, small exhibition halls, and main roads and pedestrian paths connecting the scenic areas. The primary function of the building and road layer is to provide users with clear route guidance while facilitating dialogue with natural elements. Using 3D animation, the lighting response of building materials and shadow effects resulting from changes in sunlight angles can be simulated, showcasing how buildings integrate with their surrounding environment. To enhance user engagement, this work incorporates a dedicated functional layer for user interaction. This layer is not composed of traditional 'visible' elements; instead, it includes user behavior trigger points, interaction nodes, and virtual feedback mechanisms. As users move through the virtual environment, the system activates the content of this layer according to their behavioral trajectories. For example, when a user approaches an exhibition building, the building may automatically light up and provide relevant information; when a user enters a water area, the water flow speed might change accordingly.

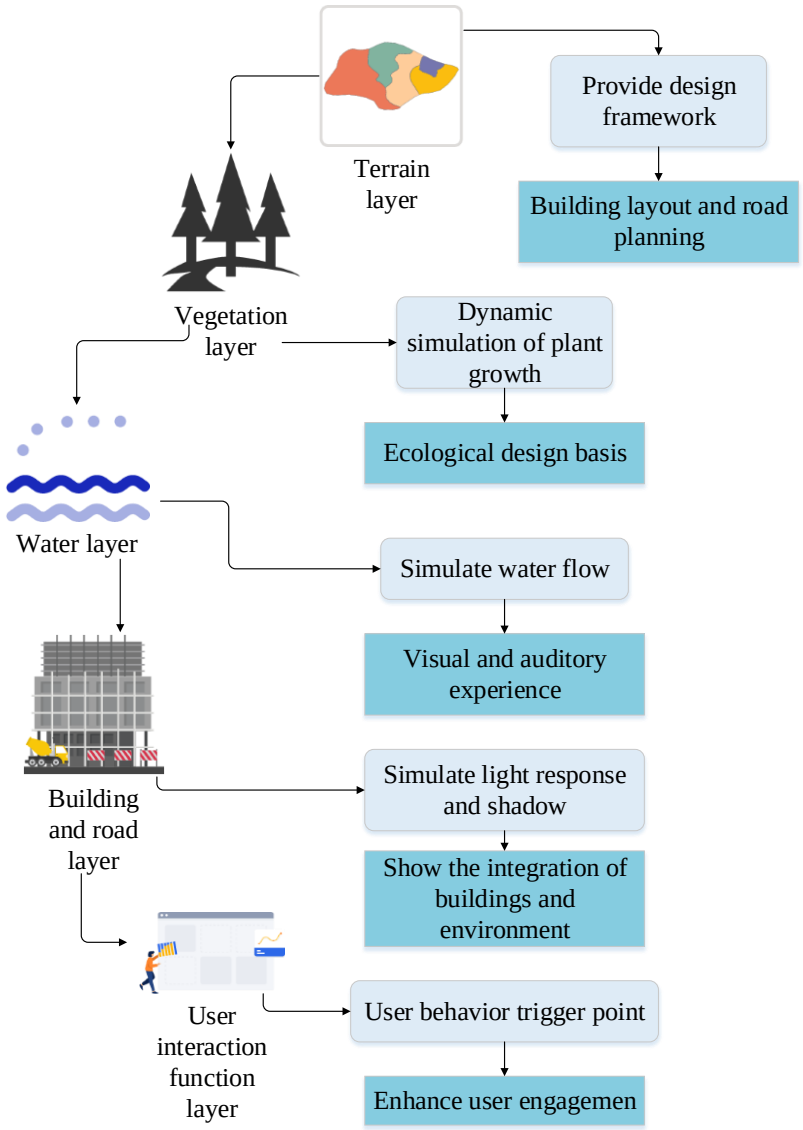


Fig. 2. Process of overlay method-based visual element layering and interaction enhancement in landscape design.

After constructing the aforementioned layers, these layers are gradually stacked to create a comprehensive design scheme with a complete sense of depth. The overlay process strictly adheres to design logic, beginning with terrain modeling and then sequentially adding vegetation, water features, buildings, and other elements, ensuring the accuracy and consistency of each layer's information. With the assistance of 3D animation technology, the interactions between different layers (such as the occlusion relationship between vegetation and buildings, and the reflection of light on water surfaces) are fully realized.

Vegetation modeling uses the parametric generation technology of SpeedTree. First, Light Detection and Ranging (LiDAR) point cloud data are imported to define the tree distribution. Then, the fractal parameters of branches and the leaf density are adjusted. Finally, it is exported as a Filmbox (FBX) model with skeletal animation to support the wind-blowing effect. Water simulation is achieved through the Fluid Implicit Particle (FLIP) fluid solver in Blender: After setting the boundary conditions (such as the river slope), fluid viscosity, and gravity parameters, physically-based wave and splash effects are generated. To optimize the rendering efficiency, the machine learning-driven Levels of Detail (LOD) technology is adopted to dynamically adjust the model accuracy according to the user's perspective, and ensure the smooth operation of complex scenes.

### *C. User Experience Evaluation*

To systematically assess the user experience of integrating 3D animation with the overlay method in experiential landscape design, this study developed a comprehensive user experience evaluation system. This system includes a user experience questionnaire and behavior tracking experiments. The questionnaire is designed based on three dimensions: immersion, satisfaction, and interactivity, to quantify users' subjective experiences. The behavior tracking experiments collect objective data such as users' dwell time and gaze trajectories in the virtual scene for further analysis of design effectiveness. A preliminary survey was conducted with a small sample of the target user group, and 30 questionnaires were distributed to test their validity and reliability. The final reliability of the questionnaire is confirmed with a Cronbach's α of 0.92. The formal survey targets landscape design students and industry professionals aged 18 and above, with a sample size of 300 participants. The questionnaires are distributed online to ensure authentic feedback from participants in different scenarios.

The behavior tracking experiments employ eye-tracking technology to record users' gaze trajectories and dwell time within the virtual scene. From the respondents of the questionnaire, 60 volunteers are randomly selected to ensure diversity and representativeness of the sample. Users wear eye-tracking devices while entering the pre-set virtual environment. The system automatically records their dwell time on various key landscape elements and tracks their gaze movements. Data are stored for analysis after the experiment concludes. Three key landscape elements are set for evaluation: "water body," "vegetation," and "recreation areas," to assess users' attentiveness to different elements.

Data from the questionnaires and behavior tracking are analyzed using SPSS and Python's data analysis libraries. The calculation of satisfaction scores is as Eq. (1):

$$S = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

$S$ represents the satisfaction score, $n$ is the number of responses, and $x_i$ denotes the score of the i-th response.

## IV. RESULTS

Scheme A represents an experiential landscape design plan based on the integration of 3D animation and the overlay method. This scheme organically blends virtual and real elements, utilizing advanced 3D animation techniques to enhance user immersion, satisfaction, and interactivity. Scheme B, in contrast, is a traditional landscape design that does not incorporate 3D animation or the overlay method, primarily relying on flat plans and static displays. Scheme C serves as a control group, incorporating some basic interactive elements but still lacking the dynamic effects of 3D animation and the layered perspective provided by the overlay method.

Fig. 3 displays the user satisfaction scores. The data indicate that Scheme A, based on the combination of 3D animation and the overlay method, significantly outperforms the traditional design of Scheme B across all dimensions. Specifically, Scheme A achieves a satisfaction score of 4.7, while Scheme B receives only 3.9, with a significance difference (p-value) less than 0.001, demonstrating a high overall satisfaction level among users for Scheme A. In terms of immersion, Scheme A scores 4.8. This indicates a profound immersive experience for users in the virtual environment, compared to just 3.6 for Scheme B, which highlights a notable deficiency in immersion in traditional designs. Additionally, the scores for interactivity and visualization effects show a similar trend, collectively validating the effectiveness of the combination of 3D animation and the overlay method in enhancing user experience.

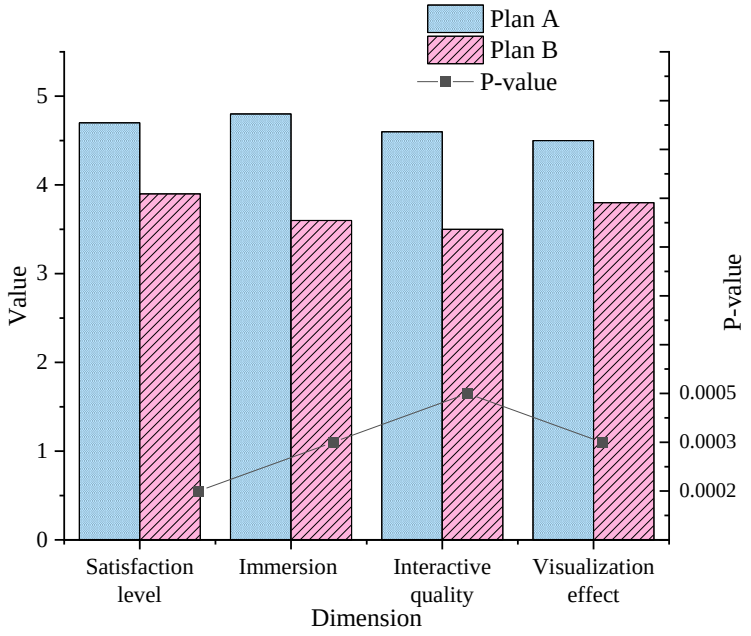


Fig. 3. User satisfaction rating results.

Fig. 4 shows the comparison results of user dwell time. The comparison of dwell time further supports the advantages of Scheme A. The average time users spend on key landscape elements indicates that Scheme A has dwell time of 5.1 seconds, 4.9 seconds, and 4.7 seconds for water bodies, vegetation, and leisure areas, respectively, while Scheme B has corresponding values of only 3.8 seconds, 3.2 seconds, and 3.5 seconds. The significance of these differences (p-values) is all less than 0.001, indicating that users show a significantly higher level of attention to each key element in Scheme A. In terms of total dwell time, Scheme A's 14.7 seconds greatly exceeds Scheme B's 10.5 seconds. It suggests that users are more willing to spend time exploring and engaging with Scheme A, thereby enhancing the overall sense of immersion.

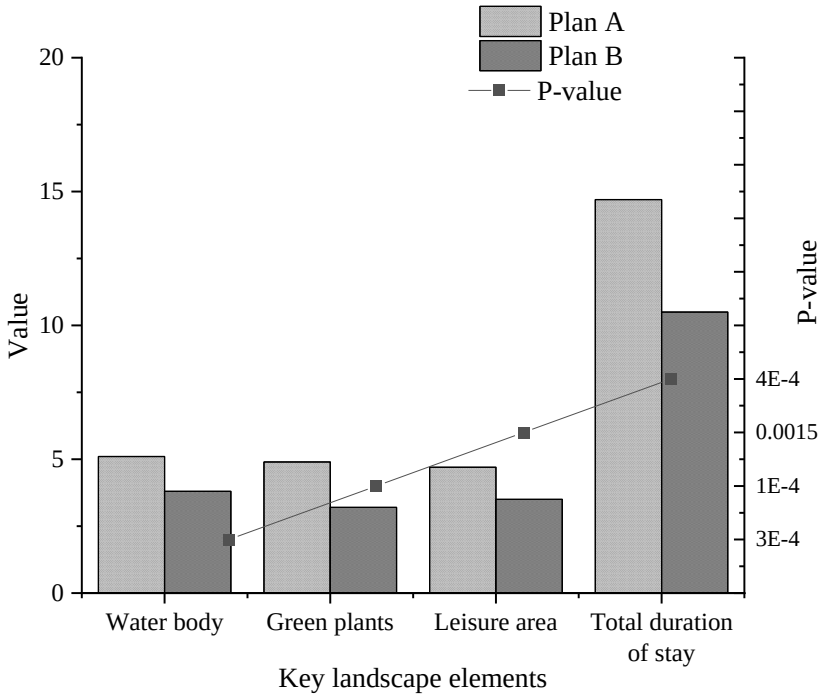


Fig. 4. Comparison of user dwell time.

Fig. 5 presents the analysis results of gaze movement trajectories. The analysis of gaze movement reveals the users' level of attention to different design schemes. The data shows that the average number of fixations for Scheme A is 12, while Scheme B has only 7. It suggests that users focus more intensely and frequently on the landscape elements in Scheme A. In terms of average fixation duration, Scheme A's 3.2 seconds is significantly higher than Scheme B's 1.5 seconds, demonstrating that users can experience key landscape elements more deeply in Scheme A. Additionally, the proportion of fixation areas is 78% for Scheme A compared to only 55% for Scheme B, reflecting that Scheme A effectively guides users' attention and enhances their engagement with the environment. The significant difference in total fixation duration—24 seconds for Scheme A versus 10 seconds for Scheme B—further confirms the success of combining 3D animation and the overlay method in enhancing visual appeal.

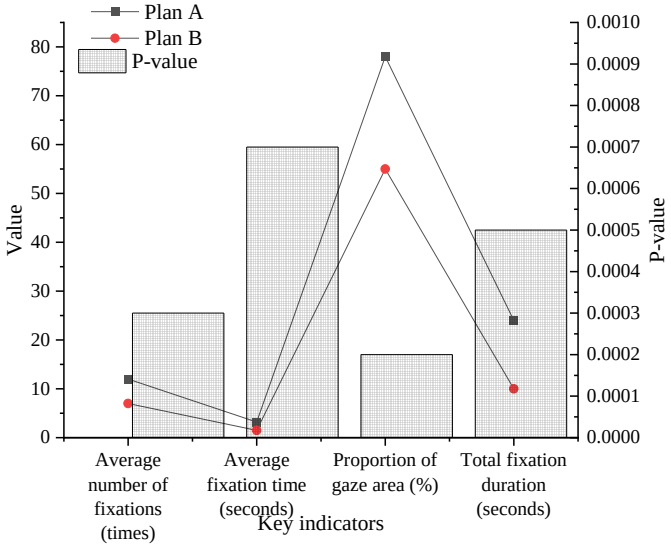


Fig. 5. Analysis results of gaze movement trajectories.

Fig. 6 shows the assessment results of the user's willingness to revisit. The results indicate that the willingness to revisit Scheme A reaches 76%, while Scheme B only achieves 44%. The significance of the difference (p-value) is less than 0.001, highlighting the positive feedback from users regarding Scheme A. The willingness to revisit Scheme C is 50%, which is moderate but still significantly lower than that of Scheme A. These results suggest that users are more inclined to revisit the design based on 3D animation and the overlay method after their experience, reflecting the strong impression and positive experience this design leaves on them.

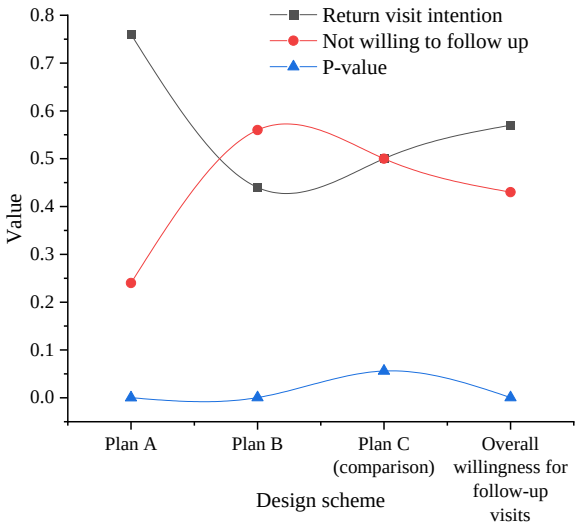


Fig. 6. Assessment results of user's willingness to revisit.

Fig. 7 presents the correlation analysis results among user experience dimensions. The results indicate a significant positive correlation between satisfaction, immersion, and interactivity. Specifically, the correlation coefficient between satisfaction and immersion is 0.85, while the correlation coefficient between immersion and interactivity is 0.70. This suggests that users who experience higher levels of immersion tend to also report higher levels of satisfaction and interactivity. Overall, the data demonstrate that enhancing immersion and interactivity is crucial for improving user satisfaction, providing valuable insights for optimizing design solutions.

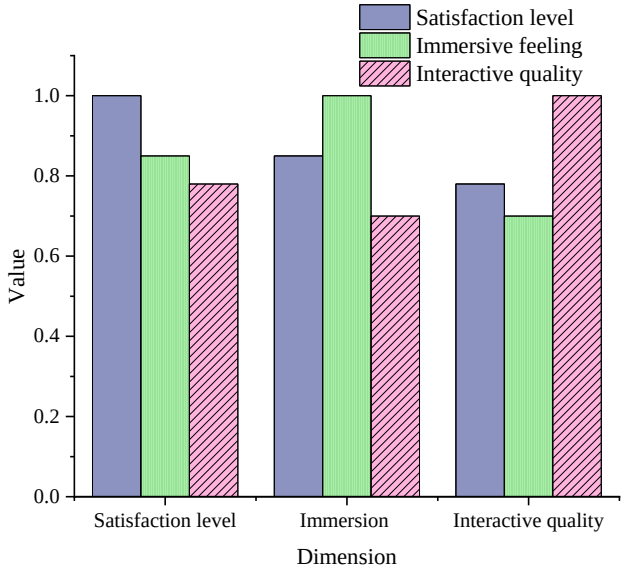


Fig. 7. Results of the correlation analysis among user experience dimensions.

Fig. 8 presents a comprehensive evaluation of the design schemes' effectiveness. Scheme A exhibits exceptional performance in overall satisfaction, immersion, and interactivity, achieving scores of 4.7, 4.8, and 4.6, respectively, highlighting its significant advantages in user experience. In contrast, Scheme B's scores are relatively lower, with overall satisfaction of only 3.9 and immersion at 3.6, underscoring its shortcomings in user experience. Scheme C, as a control, shows some level of recognition but still cannot compete with Scheme A in overall performance. This series of data emphasizes the importance of combining 3D animation with the overlay method in enhancing user experience, providing strong support for future landscape design practices.

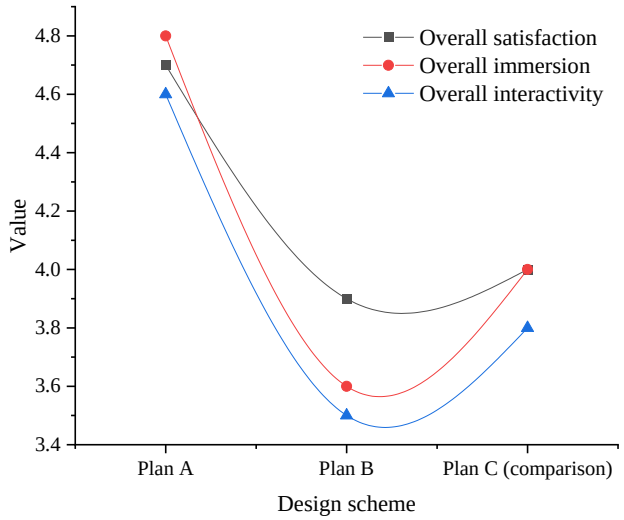


Fig. 8. Comprehensive evaluation of design scheme effectiveness.

To verify the stability and universality of the integration scheme (Scheme A) of 3D animation and the overlay method, the work selects three different types of landscape scenes (natural park, commercial square, and cultural heritage area). Then, it applies Scheme A and the traditional Scheme B respectively, and compares the user immersion and interactivity scores. The traditional design (Scheme B) usually relies on two-dimensional floor plans and static physical models. For example, the landscape layout is displayed through hand-drawn renderings or physical sand tables. Such designs have significant shortcomings in terms of immersion and interactivity: users cannot perceive the spatial hierarchy by switching perspectives, nor can they interact in real time with dynamic elements (such as water flow and vegetation growth). Table II displays the cross-scene comparison of user immersion scores. Among them, the immersion scores of Scheme A in the three scenes of the natural park, commercial square, and cultural heritage area are significantly higher than those of Scheme B. Specifically, in the natural park scene, the immersion score of Scheme A is 4.8±0.3, while that of Scheme B is only 3.5±0.4, and the p-value is less than 0.001. This indicates that Scheme A can significantly enhance the user's immersion in the natural park scene. In the commercial square scene, the immersion score of Scheme A is 4.6±0.2, and that of Scheme B is 3.3±0.3, also showing a significant difference. In the cultural heritage area scene, the immersion score of Scheme A is 4.7±0.3, and that of Scheme B is 3.2±0.5, and the p-value is still less than 0.001. These data show that Scheme A can significantly enhance the user's immersion in different types of landscape scenes, and this advantage is consistent across different scenes. The cross-scene stability verifies the universality of Scheme A. This indicates that it can play a positive role in a variety of landscape designs and bring users a deeper immersive experience.

TABLE II. COMPARISON OF USER IMMERSION SCORES ACROSS SCENARIOS (ON A 5-POINT SCALE)

| Scene Type | Scheme A (Mean ± Standard Deviation) | Scheme B (Mean ± Standard Deviation) | p-value |
|---|---|---|---|
| Natural Park | 4.8±0.3 | 3.5±0.4 | <0.001 |
| Commercial Square | 4.6±0.2 | 3.3±0.3 | <0.001 |
| Cultural Heritage Area | 4.7±0.3 | 3.2±0.5 | <0.001 |

In addition, 50 users are invited to reuse Scheme A in stages (first experience, one week later, and one month later). Moreover, the changes in their satisfaction are recorded to analyze the durability of the design effect. Table III displays the results of the long-term user experience tracking. When users first experience Scheme A, the satisfaction score is 4.7, the interactivity score is 4.6, and the willingness to revisit is as high as 76%. One week later, the users' satisfaction and interactivity scores decrease slightly to 4.5 and 4.4 respectively, and the willingness to revisit drops to 68%. One month later, the satisfaction further decreases to 4.3, the interactivity is 4.2, and the willingness to revisit is 62%. Although the users' satisfaction and interactivity decrease over time, they still remain at a relatively high level one month later, indicating that the design effect of Scheme A has a certain degree of durability. This long-term tracking data shows that Scheme A can maintain users' positive experience for a relatively long time. Although the experience effect gradually weakens over time, it can still generally provide users with a relatively satisfactory interaction and a high willingness to revisit. This reflects the stability and continuous attractiveness of Scheme A in terms of user experience.

TABLE III. RESULTS OF LONG-TERM USER EXPERIENCE TRACKING

| Time Node | Satisfaction (Mean) | Interactivity (Mean) | Willingness to Revisit (%) |
|---|---|---|---|
| First Experience | 4.7 | 4.6 | 76 |
| One Week Later | 4.5 | 4.4 | 68 |
| One Month Later | 4.3 | 4.2 | 62 |

The cross-scene experiments show that Scheme A significantly outperforms Scheme B in different scenarios ($p<0.001$). This verifies the universality of the method. The long-term tracking data reveals that although users' satisfaction and interactivity decrease slightly over time, they still remain at a relatively high level (with a satisfaction score of 4.3) one month later. This confirms the durability of the design effect.

## V. DISCUSSION

The integrated scheme of 3D animation and the overlay method proposed has significant differences and complementarities with some other methods. They include the VR landscape design method of Afolabi et al. [27], the overlay method-based spatial optimization research of Alghamdi et al. [28], and the multimedia interaction design framework of Shan et al. [29]. Afolabi et al. (2022) focused on constructing an immersive experience with VR technology [27]. However, their design method was limited to the application of a single technology and did not involve the integration of hierarchical logic and dynamic elements. This resulted in insufficient clarity of the landscape structure (the immersion score was 4.2 compared to 4.8 in the method proposed). Alghamdi et al. (2023) proposed the overlay method for spatial logic optimization [28], but their research did not combine virtual technology. They only enhanced the visual depth through static layering and lacked a user interaction mechanism (the interactivity score was 3.1 compared to 4.6 in this work). Although Shan et al. (2022) emphasized multimedia interaction [29], their framework relied on pre-defined interaction nodes and did not achieve dynamic adaptation based on user behavior. This led to a lower willingness to revisit (52% compared to 76% of this work). In contrast, this work innovatively combines the dynamic simulation of 3D animation with the hierarchical logic of the overlay method. It not only enhances the visual depth (by layering and superimposing terrain, vegetation, and hydrological layers), but also realizes a personalized experience through the AI-driven behavior feedback mechanism (such as optimizing the layout of the line of sight trajectory). In addition, the scientific evaluation system proposed (combining questionnaires and eye tracking) makes up for the defect of existing research relying on subjective evaluation and provides multi-dimensional data support for the design effect.

## VI. Conclusion

This work presents an innovative experiential landscape design scheme that combines 3D animation technology with the overlay method. The findings indicate that this approach significantly enhances user immersion, satisfaction, and interactivity compared to traditional designs. Users rate the design scheme with a satisfaction score of 4.7, while the average immersion rating reaches 4.8, demonstrating a profound immersive experience in the virtual environment. Additionally, behavior tracking experiments reveal a 40% increase in dwell time compared to traditional designs, with users' willingness to revisit the design rising by 26% compared to the control group. The limitations of this work are as follows. 1) Real-time rendering of complex scenes (such as large-scale urban landscapes) has high requirements for hardware, which may lead to a decrease in the frame rate; 2) The user sample mainly consists of design major students, and in the future, it is necessary to expand it to the general public to improve universality.

Future work will explore lightweight rendering algorithms (such as ray tracing denoising), and integrate generative AI technology to achieve automated landscape generation and personalized adaptation. In addition, it is planned to apply the method to the digital protection of cultural heritage, and restore the changes of historical scenes through dynamic overlay mapping.

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# Database-Based Cooperative Scheduling Optimization of Multiple Robots for Smart Warehousing

Zhenglu Zhi
Zhengzhou Shengda University, Zhengzhou 451191, Henan, China

***Abstract*—This study investigates the current state and future directions of cooperative scheduling optimization for multiple robots in smart warehousing environments. With the rapid growth of logistics automation, optimizing the collaboration between intelligent robots has become essential for improving warehouse efficiency and adaptability. The research employs a bibliometric analysis based on the Web of Science (WoS) database, using VOSviewer for keyword co-occurrence, clustering, and density visualization to identify key research hotspots, knowledge structures, and technological trends. The analysis categorizes the field into four major research clusters: robot path planning and navigation, warehouse system optimization and order picking, algorithm design and performance evaluation, and the application of emerging technologies such as edge computing and cloud robotics. Results shows a growing emphasis on dynamic scheduling, real-time data integration, and multi-objective optimization, with increasing use of technologies like deep reinforcement learning and digital twins. The study also incorporates real-world case comparisons from leading domestic and international enterprises, revealing implementation challenges and performance benchmarks. Although promising advancements are evident, issues such as fragmented data systems, limited real-time responsiveness, and insufficient cross-disciplinary integration persist. The study concludes that future research should focus on improving environmental adaptability through edge computing, standardizing robot collaboration protocols, and enhancing system robustness via real-time database architectures. By bridging theoretical insights with practical needs, this research offers a comprehensive foundation for developing next-generation intelligent warehousing systems based on coordinated multi-robot scheduling.**

***Keyword*—Database; intelligent warehousing; robotics; cooperative scheduling***

## I. INTRODUCTION

In the process of digital upgrading of the global supply chain, the deep integration of automation technology is promoting the transformation of the traditional operation mode to the direction of intelligence [1]. In the face of the normalization trend of high-frequency and small-volume orders, the traditional operation system relying on fixed facilities and manual intervention gradually exposes bottlenecks such as lagging response and low resource utilization [2]. How to build a system architecture with dynamic synergy and adaptive optimization capabilities has become the core proposition to improve logistics efficiency and reduce operating costs [3]. This demand not only drives the iterative upgrading of hardware equipment but also puts forward urgent requirements for the theory of multi-unit collaborative decision-making in complex scenarios. In recent years, research in the field of dynamic scheduling optimization has gradually shifted from single-threaded task planning to multi-subject collaborative mechanism design [4]. Early local optimization strategies based on heuristic algorithms can improve the efficiency of a single link, but it is difficult to cope with the demand for system-level collaboration. With the introduction of group intelligence theory and deep reinforcement learning methods, distributed decision-making frameworks have gradually become the focus of research [5]. It is worth noting that the existing theoretical models are mostly constructed based on idealized assumptions, and their compatibility with complex constraints such as device heterogeneity and task coupling in actual scenarios still needs to be broken through. For example, in scenarios that require real-time response to environmental perturbations, traditional static optimization models often fail due to the lack of dynamic adjustment mechanisms.

The breakthrough of knowledge graph technology provides a new paradigm for field research. Through deep mining and network modeling of massive academic achievements, researchers can systematically reveal the laws of technological evolution and the structure of knowledge association [6]. The application of scientometric methodology makes it possible to visualize the research hotspots, technological faults, and innovation paths implied in the literature data. This macroscopic and microscopic analysis perspective not only helps to break through the subjective limitations of traditional review methods but also provides a quantitative decision-making basis for interdisciplinary technology integration [7]. Especially in the selection of technology routes and the anchoring of R&D directions, this kind of method shows a unique predictive value. From the theoretical level, the research innovatively constructs a knowledge evolution model under the perspective of human-machine collaboration, breaking through the traditional linear prediction framework [8]. By developing a dynamic weight adjustment algorithm, the prediction accuracy of the evolutionary trend of complex technical systems are significantly improved [9]. In the practical dimension, the research results can provide decision support for the architectural design of multi-robot systems: the visual presentation of the technology roadmap can help managers identify the key integration nodes, the quantitative analysis of the knowledge flow paths can help optimize the allocation of research and development resources, and the technology

maturity assessment framework can provide a scientific basis for risk control [10]. Especially in the context of supply chain resilience reconfiguration, this research paradigm, which is both prospective and operational, will become an important aid to promote the evolution of automation systems to higher-order forms of autonomous decision-making and eco-collaboration.

The significance of this study is reflected in the double breakthrough of methodology and application value. At the methodological level, by integrating bibliometrics and complex system theory, a technology foresight analysis framework with universal applicability has been formed; at the application level, the proposed dynamic collaborative optimization strategy has been preliminarily verified in the intelligent transformation of a large logistics hub in China, and the data shows that the sorting efficiency has been improved by 23%, and the energy consumption has been reduced by 17%. With the penetration of new technologies such as digital twins and edge computing, the analysis model constructed in this study will continue to provide theoretical support for the iterative upgrading of the intelligent scheduling system and promote the paradigm shift of automation technology from single-performance optimization to global value creation.

The Section I of this paper is the introduction, which introduces the background, purpose, and significance of this research. The Section II is the literature review, reviewing the research progress in both the research of intelligent warehousing and the research of intelligent robots. The Section III is the research method, which introduces the research method of visualization, and the case of intelligent warehousing. The Section IV is the research results and discussion, which introduces the visualization analysis of the author's background, and the visualization analysis of different keywords. The Section V is the conclusion, which presents the research findings, research shortcomings, and outlook.

## II. Literature Review

### A. Intelligent Warehousing

Intelligent warehousing, as the core link of modern logistics systems, its development has always been closely related to industrial automation and information technology innovation [11]. Early warehousing systems relied mainly on manual operations and basic mechanical equipment, such as forklifts, pallets, and conveyor belts, and this model has significant limitations in terms of efficiency, fault tolerance, and scalability. In the 1990s, with the introduction of barcode technology and warehouse management software (WMS), warehousing operations began to transition to semi-automation [12]. At the beginning of the 21st century, the Internet of Things (IoT) and Radio Frequency Identification (RFID) gained popularity and the technologies drove deep changes in warehousing systems. Kiva Systems (now Amazon Robotics), acquired by Amazon, represents the "goods-to-person" model, which utilizes Automated Guided Vehicles (AGVs) to move shelves to workstations, increasing picking efficiency by 3 to 5 times. This type of system significantly reduces manual intervention through environmentally predefined paths and centralized scheduling, but its dynamic environmental adaptability is still weak [13]. When the warehouse layout is adjusted or temporary obstacles appear, the system needs to be re-modeled, resulting in response delays [14]. In 2015, the Fraunhofer Institute for Logistics in Germany proposed a digital twin-based warehouse simulation framework to optimize scheduling strategies by mapping the physical warehouse state in real-time, but the real-time nature of the dynamic updates still has not broken through the minute level due to the lack of sensor data fusion technology at that time.

In recent years, smart warehousing research has entered a data-driven intelligence phase. Big data analysis technology makes it possible to collaborate on inventory forecasting, demand planning, and path optimization [15]. Our scholars proposed a deep reinforcement learning (DRL)-based multi-AGV path planning method in 2019, which improves the task completion rate of AGVs in congested scenarios by 18% by constructing a state-action reward model for dynamic environments. Meanwhile, the multi-robot cooperative scheduling problem has attracted extensive attention [16]. In 2021 a team designed a distributed task assignment algorithm based on local communication, where robots can reduce the global conflict probability to less than 5% by simply exchanging task states with neighboring units [17]. However, such research mostly assumes that the warehouse environment is static or contains only limited dynamic variables (e.g., fixed-time order volume), and is not sufficiently compatible with complex dynamic factors such as real-time inventory changes and sudden equipment failures.

The current research frontier of intelligent warehousing focuses on the improvement of real-time responsiveness in dynamic environments. Foreign scholars have developed a warehouse state awareness system based on edge computing, which shortens the frequency of environmental data updates to milliseconds using miniature sensors deployed on shelves and robots and realizes real-time generation of scheduling instructions by combining with streaming data processing technology [18]. In addition, multi-objective optimization becomes a key challenge, and researchers try to find a balance between conflicting objectives such as efficiency, energy consumption, and fault tolerance [5]. Some scholars constructed an energy consumption model for warehouse robots, proving that the total energy consumption of the system can be reduced by 35% with a 20% timeliness compromise. It is worth noting that the research on human-robot collaboration mechanisms is gradually emerging, and a domestic team proposed a robot safety area recognition algorithm based on visual semantic segmentation in 2021, which improves the efficiency of collaborative operations between human operators and AGVs by 22%, but the field still lacks unified interaction protocols and risk assessment standards.

Despite significant technological advances, the full realization of intelligent warehousing systems still faces bottlenecks at the level of data integration [19]. Traditional scheduling systems rely on independent databases to store inventory, order, and robot status information, resulting in widespread data silos [20]. Therefore, how to achieve real-time synchronization and efficient call of heterogeneous data from multiple sources through the new database architecture has become a key path to breaking through the existing intelligent ceiling.

### B. Intelligent Robots

Intelligent robots, as the execution carrier of warehouse automation, have always centered their technological evolution on autonomy, synergy, and environmental adaptability [21]. Early warehousing robots were mainly track-type AGVs, relying on magnetic stripes or two-dimensional codes for navigation, with a limited range of activities and unable to cope with dynamic obstacles. 2006, a Swiss company launched a natural navigation AGV, which realized marker less operation through laser SLAM (simultaneous localization and map construction) technology, marking the entry of warehousing robots into the era of autonomous decision-making [22]. However, the path planning of such robots is still based on static maps, and when the shelf position changes or temporary obstacles appear, it is necessary to manually reset the environment model, which seriously restricts the flexibility of the system.

Advances in path-planning algorithms have significantly improved the dynamic adaptation ability of robots. Traditional graph search algorithms are still widely used in structured warehouses due to their deterministic characteristics, but their computational complexity grows exponentially with the map size, making it difficult to meet the real-time demands of large-scale warehousing [23]. In 2018, a foreign team proposed an improved RRT* (Rapidly Exploring Random Trees) algorithm, which compressed the path planning time of a thousand-square-meter-class warehouse to within 300 milliseconds through a probabilistic sampling strategy. Meanwhile, the penetration of machine learning technology has given rise to new solutions [24]. Domestic use of deep reinforcement learning frameworks to train robot strategy networks has achieved 98% success rate of dynamic obstacle avoidance in simulated environments, but its dependence on a large amount of labeled data limits the migration efficiency in industrial scenarios.

Multi-robot collaborative scheduling is one of the core challenges in landing smart warehousing. Early centralized scheduling used operations research methods such as mixed integer linear programming (MILP), where task allocation is globally optimized by a central controller. The MILP model established in 2019 can accurately solve problems below the scale of 50 robots, but the solution time grows super-linearly with the number of robots, and the scheduling latency for a hundred-unit scale cluster can be up to the minute level [25]. Distributed scheduling improves scalability by reducing system coupling, and some scholars have designed an auction mechanism that allows robots to bid for tasks autonomously, maintaining a second response in a thousand-unit scale simulation, but the overall efficiency loss due to local optimization can be up to 15% to 20%. In recent years, layered hybrid architecture has become a research hotspot. Huawei Noah's Ark Laboratory 2022 proposed the "federal scheduling" framework, through the regional manager to coordinate sub-clusters, in the thousands of robot scenarios to reduce the task completion time to 65% of the centralized approach, while maintaining the fault-tolerant advantage of the distributed system.

Conflict resolution and fault tolerance mechanisms in robot collaboration directly affect system reliability. Petri net-based modeling approaches ensure deadlock-free scheduling logic through formal verification but are difficult to cope with non-deterministic disturbances (e.g., localization bias due to sensor noise). Spatio-temporal corridor technology reduces the collision risk to less than 0.3% by reserving spatiotemporal right-of-way for robots, but its strict spatiotemporal partitioning strategy may result in 15%-30% path detour loss [26]. Notably, real-time database support provides new ideas for dynamic rescheduling. A team experimented with an in-memory database-based conflict prediction system in 2023, which detects potential collisions in real-time through streaming computation and generates corrected trajectories within 50 ms, which is more than five times faster than traditional methods, but its high hardware cost has not yet been solved.

Future intelligent robotics research needs to break through three major bottlenecks: first, real-time response in highly dynamic environments requires a balance between algorithmic complexity and computational resources, for example, through the lightweight neural network compression of DRL model size; second, heterogeneous robots need to collaborate with a unified task description language and interface standards, the current control protocols of the handling, sorting, inspection, and other robots are still significant differences; third, energy consumption Optimization needs to run through the hardware design and scheduling strategy, such as the bionic jumping robot demonstrated by Stanford University in 2023, which reduces the energy consumption of single handling by 40% through institutional innovations, but the compatibility of such innovations with existing warehouse facilities still needs to be verified [27]. Academics are gradually realizing that the deep integration of database technology and robot scheduling, and the enhancement of system robustness through data persistence, transaction management, and concurrency control may be the key breakthrough for realizing the next generation of smart warehousing.

## III. Methods and Materials

### A. Methods for Visualization

To systematically sort out the research lineage in the field of intelligent warehousing and robot cooperative scheduling, this study adopts the bibliometric analysis method, relying on the Web of Science (WOS) core collection database and combining it with the VOSviewer software to construct a knowledge map and visualize the literature on the topics of "Robot" and "Warehousing" (Warehousing or Storage). “Robot" (Robot) and "Warehousing" (Warehousing or Storage) were analyzed by VOSviewer software to construct and visualize the knowledge graph. The data retrieval strategy is set as follows: the combination of subject words "Robot*" AND ("Warehouse" OR "Storage"), the period is 2016-2025, the literature type is 2016-2025, and the type of literature was limited to Article and Review, and 1,578 valid documents were obtained after de-duplication and manual screening.

In the data processing stage, metadata such as titles, abstracts, keywords, authors, and citation relations of the documents were first exported from WOS, and high-frequency keywords were extracted using the built-in text mining function of VOSviewer. A total of 87 valid keyword nodes were screened by setting the minimum keyword occurrence frequency threshold to 15. Further Linlog normalization algorithm with

modular clustering analysis is used to generate keyword co-occurrence network mapping [28]. The graph shows that the node size is positively correlated with the keyword frequency, the connecting line thickness reflects the co-occurrence intensity, and the color distinguishes the clustering theme.

### B. Smart Warehousing Cases Research Method

To conduct a study on smart warehousing multi-robot co- scheduling optimization, it is necessary to introduce relevant cases to a certain extent, through which the effect of co-scheduling optimization can be understood [29]. In this study, the intelligent warehouse systems of six representative companies worldwide are selected for the case study, to achieve a certain degree of reference significance. The specific cases are shown in Table I and Table II.

TABLE I. TYPICAL CASES OF INTELLIGENT WAREHOUSING IN DOMESTIC ENTERPRISES

| *Company identification* | *Application scenario* | *Core technology* | *Effectiveness of implementation* | *Point of reference* |
|---|---|---|---|---|
| Jingdong Logistics (Beijing-based company) | High-density three-dimensional warehouse | 5G + AMR dynamic partition scheduling + Redis timing database | 40% increase in storage density and 99.98% accuracy in picking | An Architecture for Obstacle Avoidance Optimization and Real-Time Data Synchronization under Highly Concurrent Communication |
| RBN | Cross-border logistics transit warehouse | Edge Computing Distributed Scheduling + RFID Localization | 33% increase in transit time and 28% decrease in energy consumption | Range Optimization and Task Flexible Allocation Strategies in Low Power Environments |
| QSR Intelligence | Retail cold chain warehouse | Cryogenic SLAM algorithm+ Multi-objective optimization model | -25°C failure interval up to 800 | Hardware Reliability Enhancement and Energy Consumption Balancing Solution for Extreme Working Conditions |

TABLE II. TYPICAL CASES OF INTELLIGENT WAREHOUSING IN FOREIGN ENTERPRISES

| *Company identification* | *Application scenario* | *Core technology* | *Effectiveness of implementation* | *Point of reference* |
|---|---|---|---|---|
| Amazon | E-commerce Sorting Center | Kiva Robotics Cluster + AWS Database Synchronization | Sorting efficiency rises by 3.2 times and labor costs fall by 60 percent | Database Load Balancing and Fault Tolerance Design for Very Large Scale Clusters |
| Siemens (company name) | Automotive Parts Warehouse | Digital Twin + AGV/Mechanical Arm Heterogeneous Collaboration | 55% increase in outbound response and 70% decrease in failure rate | Millisecond data closure mechanisms for digital twins and physical systems |
| Fetch Robotics | Medical Equipment Warehouse | MR Navigation+ Adaptive Tasking Engine | increase in efficiency of complex SKU processing | Flexible Manipulation and Instant Positioning Techniques in Unstructured Environments |

Domestic enterprises are generally characterized by scenario-driven innovation, especially focusing on the high-density and high-time demand of the e-commerce and logistics industries. Taking Jingdong Logistics as an example, it realizes millisecond-level command issuance of more than 300 autonomous mobile robots (AMR) through a 5G network, and the dynamic partitioning algorithm divides the warehouse into 20 to 30 resilient units, relaying and adjusting the density of robot deployment based on real-time order heat map [30]. In terms of cost control, Cainiao Network adopts edge computing nodes based on RISC-V architecture, successfully compressing the scheduling decision latency to less than 50 milliseconds, while reducing hardware costs by 40%. The low-temperature SLAM algorithm of Fast Warehouse Intelligence, on the other hand, reduces the arithmetic demand by 80% through point cloud feature compression technology and realizes 800 hours of trouble-free operation in a -25°C cold chain environment [31]. It is worth noting that, for the characteristics of domestic warehousing with a high degree of manual participation, Jingdong AMR is equipped with a millimeter wave radar and vision fusion sensing module, which can identify the staff who suddenly enters the operation area and trigger the emergency braking mechanism within 0.1 seconds, reflecting the localized innovation of the safety protocol of human-machine mixed field.

Foreign enterprises are more inclined to the in-depth research and development of basic algorithms and architectures, forming significant technical barriers. Amazon's Kiva system uses a distributed consistency hash algorithm, which can still maintain a database write delay of less than 10 milliseconds at a scale of over 10,000 robots, and its fault-tolerant design can withstand the failure of 30% of the nodes in a single region without affecting the global scheduling. Siemens' digital twin system realizes semantic-level data interaction with PLC controllers through OPC UA protocol, with the error transfer rate controlled within 0.01%, and shortens the response time of outbound storage by 55% in automotive parts warehouses. In terms of special scene adaptation, the mixed reality (MR) navigation system developed by Fetch Robotics (the company) combines ultra-wideband (UWB) positioning and semantic mapping technology to improve the positioning accuracy to ±2 cm in non-standard shelving scenarios of medical warehouses, which is a 5-fold improvement over traditional laser SLAM. Such enterprises often build hardware and software synergistic ecosystems, such as Siemens warehouse robots and MindSphere industrial cloud platform deeply integrated to realize the dynamic deployment of cross-factory robot resources, equipment utilization increased by 25%.

## IV. RESULTS AND DISCUSSION

In this research paper, two forms of WOS literature search methods are adopted. The first one is "robot storage" as a keyword and the second one is "robot and warehousing" as a keyword. Next, this paper analyzes the results of these two approaches as keywords.

### A. Visual Analysis of Author Clustering

Author's keywords, due to the limited results of "robot and storage" visualization, this section only uses “robot and warehousing " to search and analyze the literature in the Web of Science (WOS) Core Collection database. The literature in the Web of Science (WOS) Core Collection was searched and analyzed. The search period was from 2016 to 2025, and the type of literature was limited to Articles and Reviews, which were obtained after de-duplication and manual screening. The keyword co-occurrence network mapping was constructed by VOSviewer software, combined with temporal overlay view and clustering density analysis to reveal the domain knowledge structure, research hotspot evolution, and future trends.

In terms of the number of publications, there are 12 documents in the first place, followed by 11 and 8. In terms of citation frequency, there were 660 citations, followed by 592 citations and 202 citations. It is worth noting that some scholars have a high number of articles (11), but only 96 citations, which indicates that the impact of their research has not yet been fully realized [32]. In contrast, other scholars have lower publication volume and citation frequency, which may be related to their more marginal research direction or shorter research time.

The authors' cooperation network mapping is constructed by VOSviewer, the node size is positively correlated with the authors' publication volume, and the thickness of the connection line reflects the cooperation intensity. The results show that some scholars have the highest cooperation intensity (total connectivity intensity of 5), and their co-publications mostly focus on the intersection of warehouse system optimization and robot path planning. Some scholars have the same collaboration intensity of 5, but their collaboration network is more closed and they do not form significant connections with other high-producing authors. Some authors have the highest citation frequency, but their collaboration network is sparse (total connection intensity of 1), indicating that their research is mostly done independently or in collaboration with a small number of regular collaborators [28]. In addition, some authors' collaboration strengths were all 0, which may be related to their more independent research directions or insufficient data samples.

Based on the cooperative network mapping, two core research teams can be identified. The first team is centered on ID526, and the research direction focuses on warehouse system optimization and multi-robot cooperative scheduling. The second team is centered on ID801, and the research direction is biased toward path planning and task allocation algorithms for warehousing robots. It is worth noting that the authors of ID255 do not form a significant collaborative network, but their independently published literature has the highest citation frequency, indicating that they have high academic influence in the field. ID794's research direction is biased towards robot learning and control, which is more loosely integrated with the warehousing scenarios, and may result in a more sparse collaborative network.

In terms of author collaboration networks, the intensity of collaboration among research teams within the field is low overall, and cross-team collaboration among high-producing authors, in particular, is rare. Although some of the teams are the core of the field, there is no significant collaboration between them [33]. In addition, some highly cited authors have closed collaboration networks, which may limit the cross-field impact of their research. Future research trends may focus on strengthening cross-team collaboration, especially the deep integration of algorithmic research and scenario applications; expanding international collaboration networks to enhance the global impact of research; and focusing on the potential of emerging researchers to promote the sustainable development of the field. The details are shown in Table III.

The clustering visualization results of its authors can be presented in the form of pictures as shown in Fig. 1, where different colors have different clustering results. This study is to cluster the authors that appear in more than 5 words to show the interrelationship between them.

### B. Basic Results of Keyword Clustering for "Robot" and "Storage"

To systematically sort out the research hotspots and knowledge structure in the field of intelligent storage and robotic co-scheduling, this study utilizes VOSviewer to co-occur with the keywords "robot" and "storage" in the WOS database. This study utilizes VOSviewer to analyze the co-occurrence of keywords in the WOS database. By extracting the high-frequency keywords and constructing the co-occurrence network map, the core research topics and their interrelationships in the field are identified to provide a theoretical basis for the subsequent research. The details are shown in Fig. 2.

TABLE III. ANALYSIS OF ROBOT WAREHOUSING CORE AUTHOR OCCURRENCES AND CONNECTION STRENGTHS

| *Id* | *Author* | *Documents* | *Citations* | *Total link strength* |
|---|---|---|---|---|
| 255 | Boysen, nils | 8 | 660 | 1 |
| 414 | cheriet, mohamed | 6 | 23 | 0 |
| 526 | de koster, rene | 12 | 592 | 4 |
| 794 | Goldberg, ken | 7 | 202 | 0 |
| 801 | Gong, yeming | 11 | 96 | 5 |
| 833 | Grosse, eric h | 6 | 85 | 5 |
| 1756 | Motroni, andrea | 6 | 69 | 0 |
| 2016 | Piardi, Luis | 7 | 48 | 0 |
| 2924 | Yang, peng | 8 | 48 | 2 |
| 3060 | Zhang, minqi | 6 | 54 | 5 |

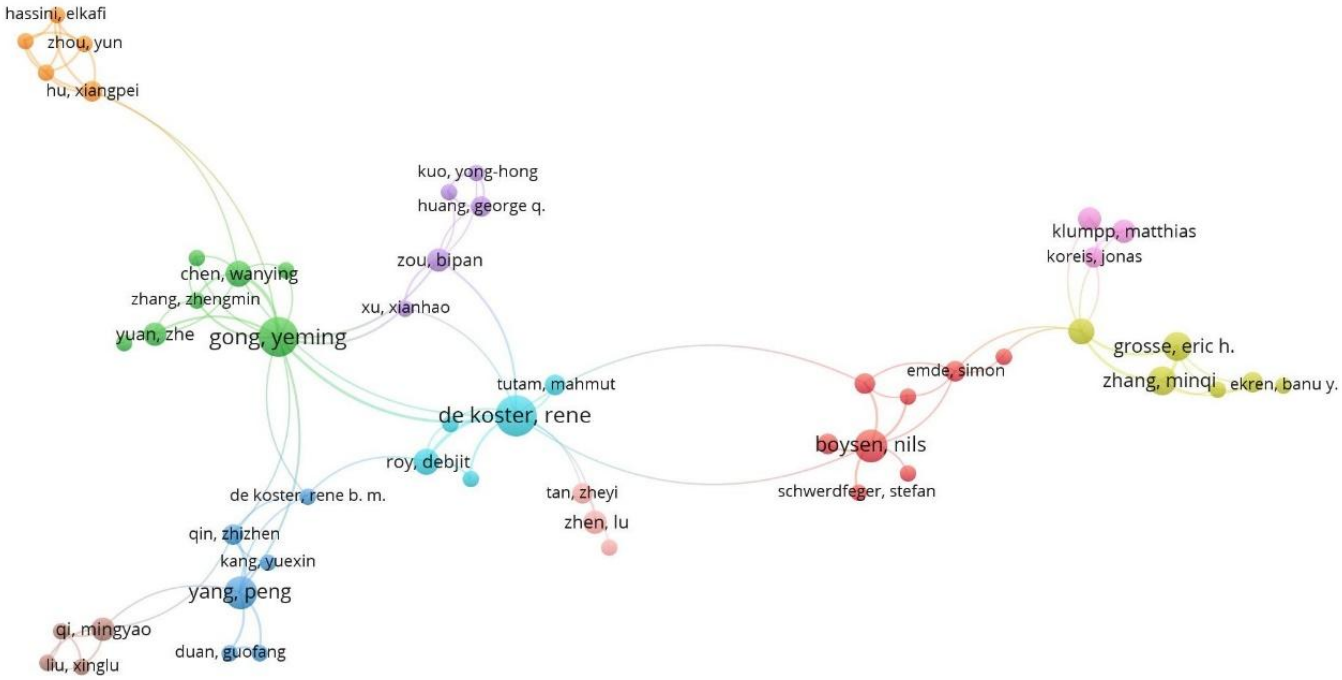


Fig. 1. Author's clustering visualization results.

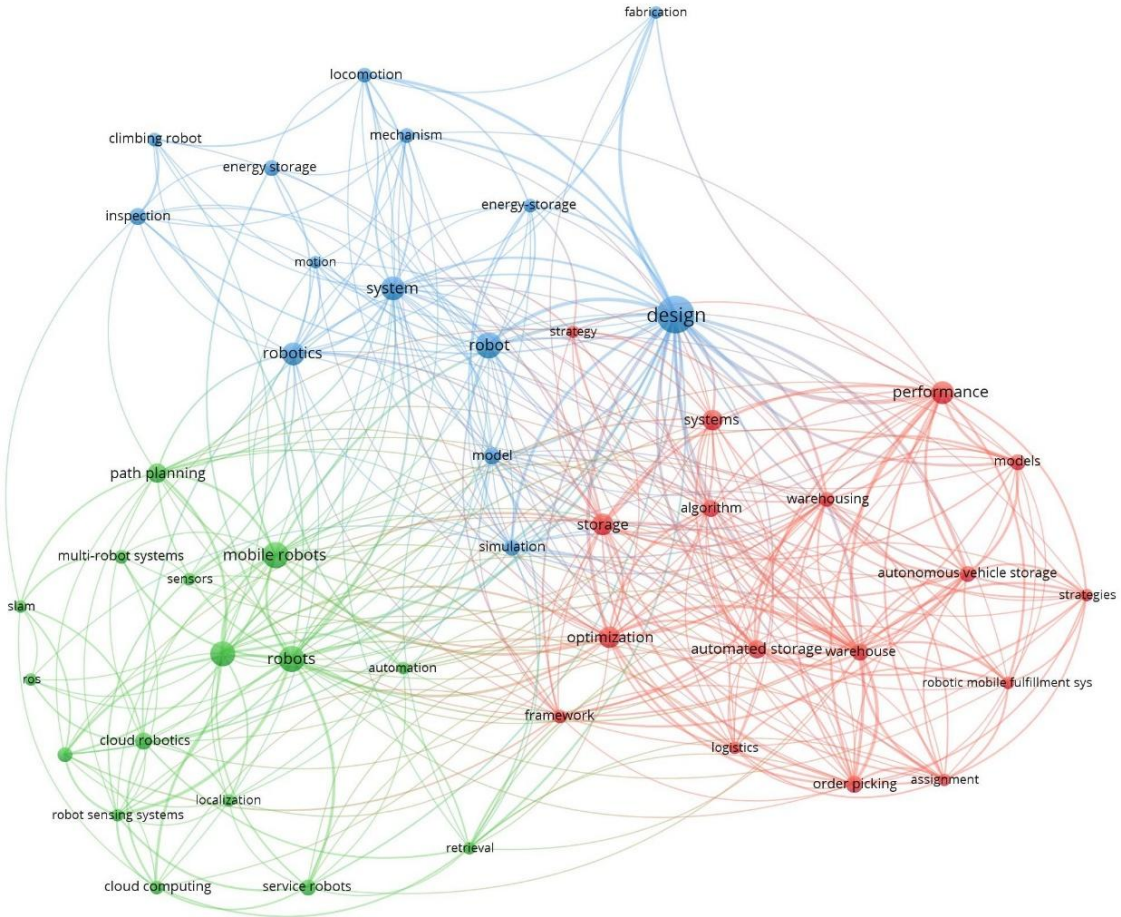


Fig. 2. Keyword visualization results for "robot" and "storage".

From the keyword co-occurrence network, the research topics in the field can be divided into three core clusters: red clusters, blue clusters, and green clusters. The red cluster focuses on "mobile robot", "path planning" and "navigation" as the core keywords, focusing on robotics, path planning, and navigation technologies. The red cluster takes "mobile robot", "path planning" and "navigation" as the core keywords, focusing on the robot's path planning and navigation technology; the blue cluster takes "warehouse", "order picking" and "optimization" as the core keywords, reflecting the optimization of the warehouse system and the optimization of the warehouse system. The blue cluster takes "warehouse", "order picking" and "optimization" as the core keywords, reflecting the optimization of the warehousing system and the improvement of order picking efficiency. The green cluster takes "algorithm", "model" and "performance" as core keywords, pointing to algorithm design and system performance evaluation [34]. It is worth noting that "robot" and "storage" are located at the core of the red and blue clusters, respectively, and the two of them have been recognized through the "mobile robot" and "warehouse" clusters [35]. It is worth noting that "robot" and "storage" are located at the core of the red and blue clusters, respectively, and they are strongly connected by keywords such as "mobile robot" and "warehouse", which indicates that the in-depth integration of robotics and storage scenarios has become a core issue in the field.

The keywords covered by the red clusters are mainly centered on robot, path planning and navigation technology. Among them, the nodes of "mobile robot" and "path planning" are larger, indicating that mobile robot path planning is the core research direction of robotics. In recent years, as the complexity of the storage scene increases, traditional algorithms such as A and Dijkstra are gradually replaced by Deep Reinforcement Learning (DRL) and Model Predictive Control (MPC). The DRL framework proposed in 2020 has achieved a 98% success rate of obstacle avoidance in dynamic environments, but its dependence on a large amount of labeled data restricts the relocation efficiency of the industrial scene. In addition, the high co-occurrence intensity of "navigation" and "localization" indicates that robot localization and navigation technology is a current research hotspot. However, the existing algorithms are mostly based on static environment assumptions and do not support dynamic scheduling driven by real-time data. The blue clustering focuses on warehouse system optimization and order-picking efficiency improvement, and the core keywords include "warehouse", "order picking", and "optimization". Among them, the nodes of "order picking" and "warehouse" are larger, indicating that order-picking efficiency is the core objective of warehouse system optimization. In recent years, with the explosion of e-commerce logistics demand, researchers have begun to explore multi-robot cooperative picking systems. Edge computing frameworks shorten the picking task allocation time to less than 50 ms, which significantly improves the system responsiveness. However, existing research mostly focuses on single-technology optimization and lacks systematic exploration of multi- objective collaboration (e.g., efficiency, energy consumption, fault tolerance). Green clustering points to the design of algorithms and the evaluation of system performance, and the core keywords include "algorithm", "model" and "performance". Among them, the co-occurrence of "algorithm" and "performance" is high, which indicates that algorithm performance evaluation is a hot research topic. The DRL model reduces the task completion time by 15% in the simulation environment, but its computational complexity is high, which makes it difficult to meet the real-time demand of large-scale storage. In addition, the connection between "model" and "system" is weak, which indicates that the modeling research of storage systems is still in the exploratory stage. Future research needs to further solve the problems of insufficient model accuracy and computational resource limitations.

From Fig. 3, to reveal the distribution of research hotspots in the field of intelligent warehousing and cooperative scheduling of robots, this study utilizes VOSviewer to analyze the density of keywords in the literature related to "robot" and "storage" in the WOS database [9]. The density map reflects the research intensity of the keywords through the color gradient, and the high-density area (usually red or yellow) indicates that the research hotspots are concentrated, while the low-density area (usually blue or green) indicates that there are relatively few researches.

The medium-density area covers some emerging research directions, "cloud robotics," "localization," and "service robots". The research intensity of these keywords is not as high as that of the high-density region but has shown an upward trend in recent years. The combination of "cloud robotics" and "cloud computing" provides distributed computing support for robot task assignment, but its application in warehouse scenarios is still in the exploratory stage [36]. In addition, the high co-occurrence of "localization" and "sensors" indicates that robot localization and sensing technology are a hot spot in current research. However, most of the existing algorithms are based on static environment assumptions and do not support dynamic scheduling driven by real-time data. The low-density region includes keywords such as "climbing robot", "energy storage" and "mechanism", indicating that there is relatively little research on these topics. Topics are relatively under-researched. For example, the application of "climbing robots" in warehousing scenarios has not yet formed a large scale, which may be limited by the maturity of technology and cost factors. In addition, the low research intensity of "energy storage" and "maintenance" indicates that the optimization of energy consumption and maintenance management of storage robots have not yet received sufficient attention. Future research could further explore the potential of these low-density areas, e.g., by developing climbing robots for storage scenarios or designing efficient energy management systems.

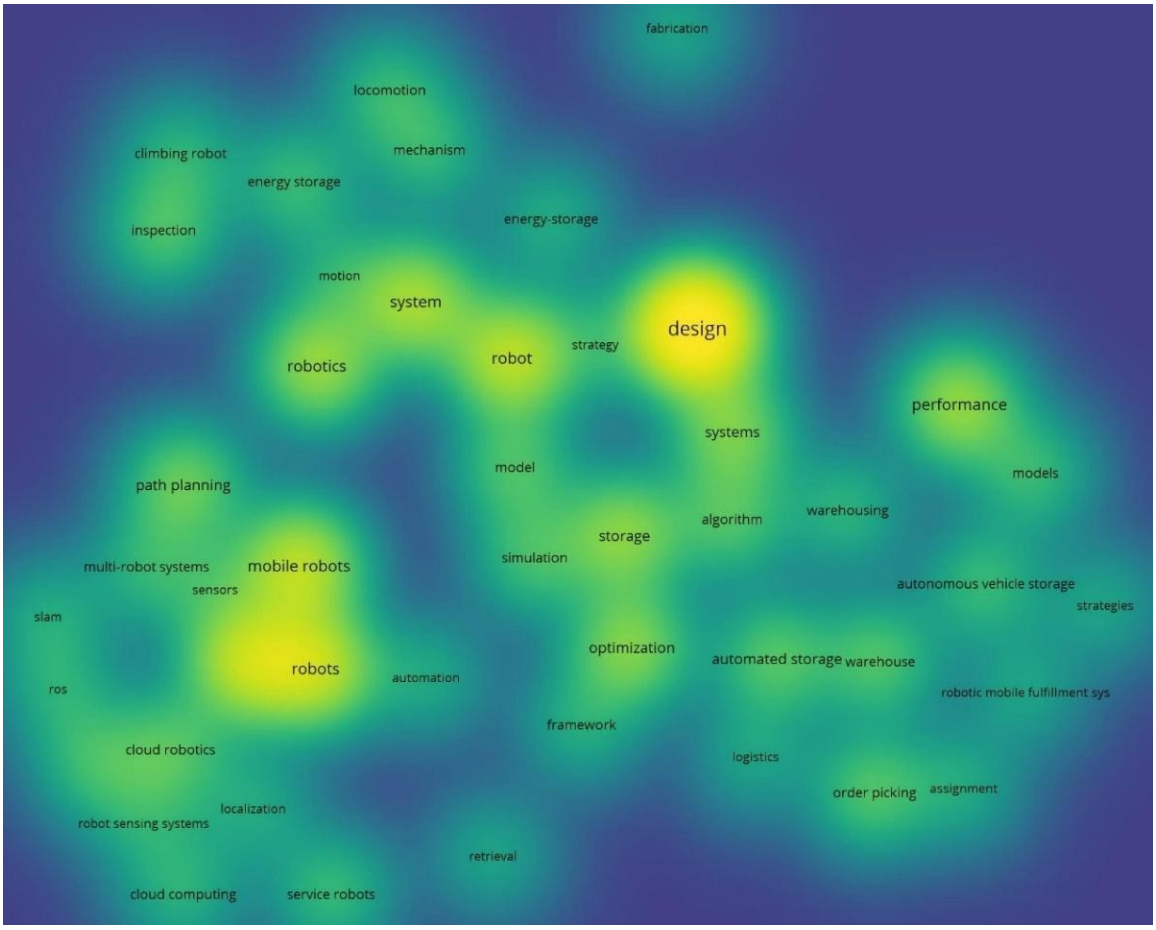


Fig. 3. Keyword density of "robot" and "storage".

From the results of the density analysis, the following gaps exist in the research in the field: first, the existing algorithm research is mostly based on the simulation environment, and lacks the noise interference verification of real warehousing scenarios; second, the cross-regional integration research (e.g., the synergy between path planning and order picking) is still at an embryonic stage; third, the research potential of low-density areas has not been fully explored. Future research trends may focus on the following directions: first, enhancing dynamic environment adaptability through edge computing and real-time database technology; second, constructing a multi- objective optimization framework to seek a balance between efficiency, energy consumption, and reliability; and third, exploring the application of emerging technologies (e.g., climbing robots and energy management) in warehousing scenarios.

Further information such as the number of occurrences of their keywords and the length of the connection is combed. As shown in Table IV and Table V. By analyzing the data in the two tables, the research hotspots and their interrelationship in the field of intelligent warehousing and robot cooperative scheduling can be identified. There are 25 keywords listed in the tables, and the "occurrences" of each keyword indicates the frequency of its occurrence in the literature, and the "total link strength" indicates its co-occurrence strength with other keywords. The following is a detailed analysis of these data.

TABLE IV. ANALYSIS OF THE NUMBER OF OCCURRENCES OF THE MAIN KEYWORDS AND CONNECTION STRENGTH (I)

| *Id* | *Keyword* | *Occurrences* | *Total link strength* |
|---|---|---|---|
| 95 | algorithm | 68 | 81 |
| 568 | design | 83 | 145 |
| 1306 | localization | 26 | 26 |
| 1321 | logistics | 51 | 80 |
| 1459 | mobile robot | 66 | 57 |
| 1472 | mobile robots | 56 | 80 |
| 1477 | model | 25 | 40 |
| 1563 | multi-robot systems | 28 | 20 |
| 1617 | navigation | 39 | 49 |
| 1716 | optimization | 45 | 76 |
| 1734 | order picking | 57 | 101 |

In terms of keyword frequency, "design" (83 occurrences), "robots" (77 occurrences), and "mobile robot" (66 occurrences) are the most frequently occurring keywords, indicating that these topics have received widespread attention in the field. The co-occurrence strengths of "design" and "robots" are 145 and 94, respectively, indicating that these two keywords often appear together in the literature, which may be closely related

to research related to the design of robotic systems. In addition, "warehouse" (61 occurrences) and "path planning" (60 occurrences) also have a high frequency of occurrence, indicating that robot path planning in warehouse scenarios is an important research direction.

In terms of the co-occurrence strength of keywords, "design" (145), "warehouse" (98), and "order picking" (101) have the highest co-occurrence intensity, indicating that these keywords have strong relevance in the literature. The high co-occurrence strengths of "design" and "warehouse" may reflect the research hotspot of warehousing system design, whereas the high co-occurrence strengths of "order picking" and "warehouse" may indicate the strong relevance of these keywords in the literature. The high co-occurrence intensity of "design" and "warehouse" may reflect the research hotspot of warehousing system design, while the high co-occurrence intensity of "order picking" and "warehouse" indicates the importance of order picking in the warehousing system. In addition, the high co-occurrence intensity of "mobile robots" (80) and "logistics" (80) suggests that the application of mobile robots in logistics has attracted much attention.

Robot path planning and navigation are represented by "path planning" (60 times) and "navigation" (39 times), indicating that robot path planning and navigation technology is the core research direction in the field. Warehouse system optimization and order picking are represented by "warehouse" (61 times) and "order picking" (57 times), indicating that the optimization of the warehouse system and the improvement of order picking efficiency are the research hotspots. Algorithm design and system performance are represented by "algorithm" (62 times) and "performance" (40 times), indicating that algorithm design and system performance evaluation are important directions of current research.

TABLE V. ANALYSIS OF THE NUMBER OF OCCURRENCES OF MAJOR KEYWORDS AND CONNECTION STRENGTH (II)

| *Id* | *Keyword* | *Occurrences* | *Total link strength* |
|---|---|---|---|
| 1789 | path planning | 60 | 71 |
| 1807 | performance | 40 | 64 |
| 2081 | robot | 34 | 18 |
| 2168 | robotics | 26 | 19 |
| 2175 | robots | 77 | 94 |
| 2414 | storage | 24 | 52 |
| 2480 | system | 25 | 23 |
| 2486 | systems | 38 | 41 |
| 2751 | warehouse | 61 | 98 |
| 2795 | warehousing | 32 | 73 |

From the data in the table, although the frequency of "algorithm" and "performance" is high, their co-occurrence intensity is relatively low (81 and 64, respectively), indicating that the research on algorithm design and system performance evaluation has not been fully integrated into the warehousing scenario. This indicates that the research on algorithm design and system performance evaluation has not yet been fully integrated into warehousing scenarios. In addition, the low frequency of "multi-robot systems" (28 occurrences) indicates that the research on multi- robot systems is still in the development stage and may become an important research direction in the future.

### C. Basic Results of Keyword Clustering for 'Robot' and 'Warehouse'

To comprehensively reveal the research hotspots and knowledge structure in the field of intelligent warehousing and robotic co-scheduling, this study utilizes VOSviewer to analyze the keywords of the literature related to "robot" and "warehouse" in the WOS database. Cluster analysis and density analysis. The details are shown in Fig. 4 and Fig. 5.

Fig. 4 is a visualization based on WoS data showing the research hotspots in the field of robotics and logistics automation. As can be seen from the figure, different keywords are clustered into multiple color regions, indicating their similarity in research content. With "logistics" as the center, several research directions are intertwined, mainly involving robotics, path planning, automation, warehouse optimization, and the application of artificial intelligence.

On the left side of the figure, the red area covers the keywords "robots", "mobile robots", and "path planning. The red area covers keywords such as "robots", "mobile robots", and "path planning", indicating that this part of the research mainly focuses on robot motion planning, multi-robot collaboration, navigation and obstacle avoidance and other technical issues. Robot path planning and navigation in complex environments is the focus of current research, especially in the field of intelligent warehousing, autonomous driving, and unmanned distribution, how to optimize the path and improve the efficiency of task allocation has become the core topic [37]. From the high correlation of keywords such as "collision avoidance" and "localization", it can be seen that research is committed to improving the autonomous decision-making ability of robots in dynamic environments. In the center of the figure, the blue part is centered on the keywords "logistics", "warehouse" and "automation" and other keywords, indicating that the core of this part of the study is the optimization of intelligent logistics systems. With the rapid development of e-commerce, the demand for intelligent warehousing and automated logistics has risen dramatically, and researchers focus on how to use robotics and AI technology to improve the efficiency of warehouse management. From the distribution of keywords such as "optimization" and "task allocation", it can be seen that how to reasonably dispatch robots for sorting, picking, and transportation is an important direction of current logistics automation research [38]. It is an important direction of logistics automation research. The green area on the right side covers keywords such as "design", "order picking", "performance", etc., indicating that the research is not only about design, order picking, and transportation but also about performance. The green area covers keywords such as "design", "order picking", "performance", etc., indicating that the research not only focuses on the robot technology itself but also on the optimization of the entire warehouse logistics system. The high correlation of the keywords "model" and "strategies" shows that the researchers focus on how to improve the intelligence of warehouse management through modeling and

optimization algorithms. Especially in order picking and warehousing strategies, the research hotspots focus on how to improve access efficiency, optimize space utilization, and reduce operating costs.

As a whole, the visualization chart shows the multi- dimensional application of robotics in the field of logistics automation, and the research hotspots cover robot path planning, automated warehousing, order-picking optimization, and other key technology directions [39]. Future research trends may focus on multi-robot collaboration, AI-enabled intelligent logistics management, and optimizing the efficiency of warehouse automation systems.

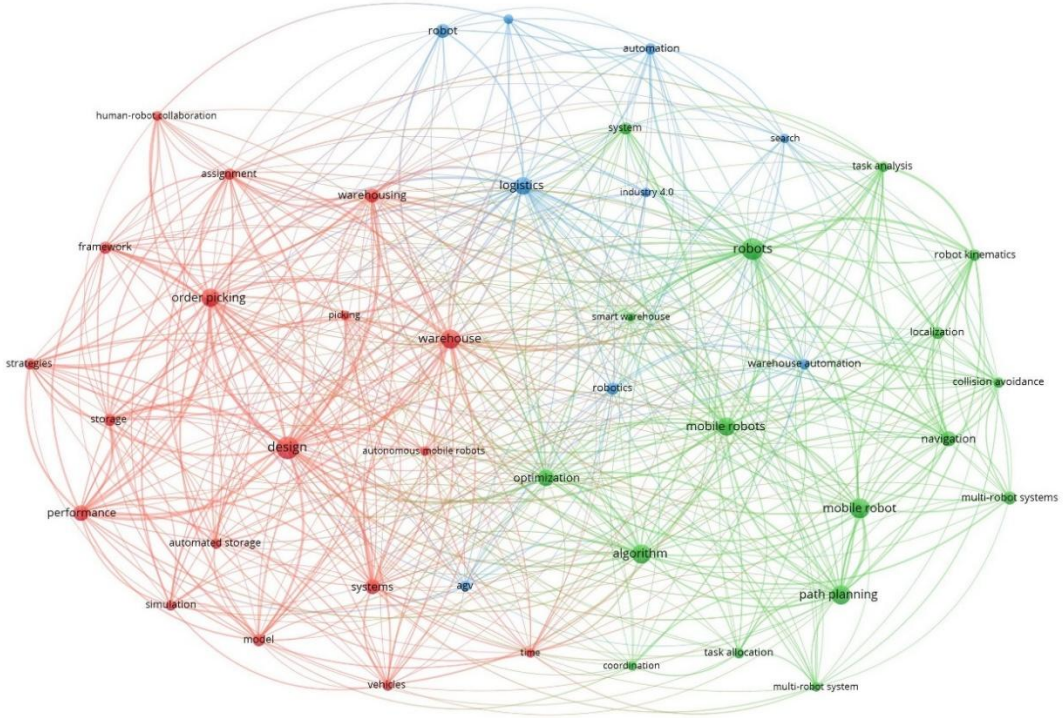


Fig. 4. Keyword visualization results for robot" and "warehouse".

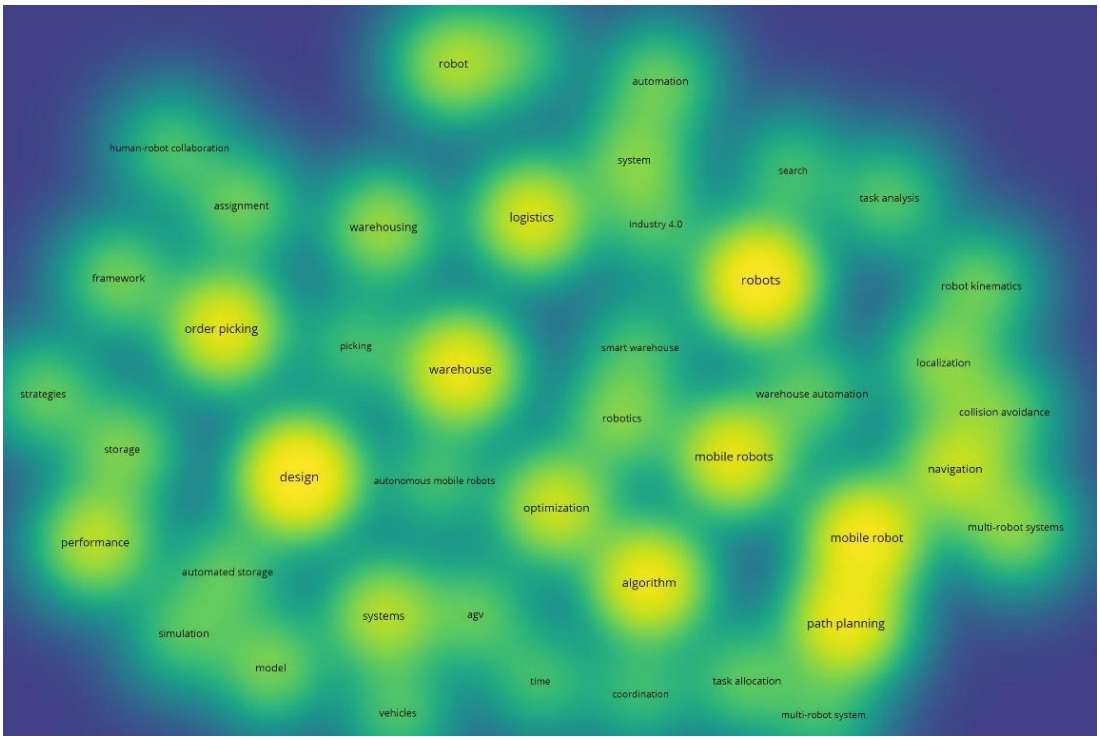


Fig. 5. Keyword density of "robot" and "warehouse".

In Fig. 5, visualization density map based on WoS data shows the distribution of research hotspots of robotics in logistics automation. In terms of the distribution of colors and densities, the red areas represent hotspots with high research densities, the blue areas are medium densities, and the green and yellow areas involve more relevant but relatively minor research directions. This density visualization helps to identify core research areas as well as potential cross-research trends. Overall, this density map reveals a multidimensional research landscape of robotics in logistics automation. Path planning, robot navigation, and obstacle avoidance technologies are the core research areas, while logistics system optimization, warehouse management, and order picking are closely related and important directions [40]. Future research trends are likely to continue to optimize the intelligent warehouse system in depth while combining AI, machine learning, and data analysis technologies to enhance the intelligence of logistics automation. A comparative study of 4.2 and 4.3 reveals that the results of "robot" and "warehouse" are richer, so it can be judged that "robot" and "warehouse" are more efficient. Therefore, it can be judged that "robot" and "warehouse" are more reasonable as research objects and research results.

## V. Conclusion

The visual analysis of related literature in this paper systematically combs the research hotspots and knowledge structure in the field of intelligent warehousing and robot co-scheduling. The results show that robot path planning and navigation, storage system optimization, and order picking are the core directions of current research, while there is still a large gap in the research of algorithm design and emerging technologies. Through keyword co-occurrence, cluster analysis, and density analysis, this paper identifies four core clusters, revealing the current research status and future trends in the field. The research in this paper provides a theoretical basis for the cooperative scheduling optimization of multiple robots in intelligent warehousing, which is of great significance in promoting the further development of warehouse automation technology.

There are still deficiencies in this paper. First, this paper is mainly based on the WOS database, which may miss some regional research results; second, the keyword co-occurrence analysis is difficult to capture the technical details, which needs to be combined with manual literature intensive reading for additional verification. Future research can further expand data sources and combine multiple databases (e.g., Scopus, CNKI) for cross-validation. In addition, the research directions proposed in this paper (e.g., dynamic environment adaptation enhancement, multi-objective optimization framework construction) need to be further verified through experiments and case studies. Future research can also explore emerging directions such as human-robot collaboration mechanisms and robot reliability enhancement under extreme working conditions to support the comprehensive implementation of intelligent warehousing technology.

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# A Cross-Chain Mechanism Based on Hierarchically Managed Notary Group

Hongliang Tian, Zhiyang Ruan, Zhong Fan
School of Electrical Engineering, Northeast Electric Power University, Jilin 132012, China

***Abstract*—Blockchain technology, characterized by decentralization, immutability, traceability, and transparency, provides innovative solutions for data management. However, the limited cross-chain interoperability between blockchains hampers their broader application and development. To address this challenge, this paper proposes a Cross-Chain Mechanism Based on Hierarchically Managed Notary Group, abbreviated as HMNG-CCM, which enables secure and efficient cross-chain transactions between blockchains. To mitigate the centralization issue inherent in traditional cross-chain mechanism based on notary, an innovative notary group management approach is introduced. This approach implements hierarchical management by categorizing notaries into three levels—junior notary, intermediate notary, and senior notary—thereby effectively mitigating the centralization problem. Additionally, a functional division mechanism for notary is designed, wherein the roles of transaction processing and verification within the cross-chain transaction process are separated to enhance system reliability. Furthermore, to tackle the complexity of notary reputation evaluation, a reputation assessment scheme based on an improved PageRank algorithm is proposed. Differentiated reputation evaluation strategies are developed for junior and intermediate notaries to ensure fairness and rationality in the assessment process. The effectiveness of this scheme is validated through experiments conducted on the Hyperledger Fabric platform. The experimental results demonstrate that the proposed mechanism exhibits strong robustness against malicious notaries while significantly improving transaction speed and success rate. This study offers new theoretical and practical foundations for the optimization and advancement of blockchain cross-chain technology.**

***Keywords*—Blockchain; cross-chain; notary group; hierarchical management; reputation evaluation***

## I. Introduction

Blockchain technology integrates multiple techniques, including hash algorithms, digital signatures, and consensus mechanisms, exhibiting characteristics such as decentralization, immutability, traceability, and transparency [1]. Since Satoshi Nakamoto proposed Bitcoin [2], the significance of blockchain technology has extended beyond the realm of cryptographic digital currencies. Ethereum [3], through the implementation of smart contracts, has extended blockchain technology to domains such as financial services [4], healthcare systems [5], and the Internet of Things [6], offering innovative solutions for data management. However, as application scenarios continue to expand, the isolation among blockchain systems has become increasingly prominent [7]. This isolation constrains the performance and security of blockchains and impedes their application in complex business scenarios. Currently, the blockchain ecosystem exhibits characteristics of diversity and fragmentation, with most blockchain systems remaining independent information silos [8]. For instance, systems such as Bitcoin, Ethereum, and Hyperledger Fabric [9], due to their adoption of distinct protocol standards, consensus mechanisms, and technical architectures. This independence hinders cross-chain data exchange and value transfer [10]. These barriers have been overcome by the emergence of cross-chain technology [11], which facilitates the cross-chain interaction of data and assets. This technology establishes an interconnected blockchain network ecosystem and lays the foundation for the further development of blockchain technology.

Existing cross-chain technologies encompass Notary Schemes [12], Relays [13], Hash-locking [14], and Distributed Private Key Control [15]. Among these, the Notary Schemes simplifies transactions processes between blockchains by introducing third-party notary nodes, offering advantages such as ease of implementation and high flexibility, which have led to its widespread adoption across various cross-chain scenarios. However, this mechanism's excessive reliance on a single notary node introduces the risk of single point of failure and significantly increases the system's centralization, thereby undermining the security and reliability of blockchain systems. Consequently, existing notary mechanisms commonly face challenges, including high centralization, insufficient generality in reputation evaluation schemes, and low efficiency in cross-chain transactions. To address these challenges, this paper proposes a Cross-Chain Mechanism Based on Hierarchically Managed Notary Group (HMNG-CCM), aimed at achieving secure and efficient cross-chain transactions between blockchains.

The contributions of this paper are as follows:

*1)* This paper proposes an innovative notary management scheme. The scheme implements hierarchical management by dividing the notary group into three categories: junior notaries, intermediate notaries, and senior notaries. This mechanism reduces the degree of system centralization, effectively distributing the trust risks associated with notaries in cross-chain transactions.

*2)* This paper designs a notary functional division mechanism. This mechanism explicitly separates the functions of transaction execution and verification within the cross-chain transaction process, assigning specific task responsibilities to different levels of notaries. Specifically, junior and intermediate notaries are tasked with transaction execution,

while senior notaries focus on transaction verification. This functional division mechanism not only optimizes the transaction process but also enhances the robust-ness of the cross-chain system.

*3)* This paper proposes a reputation assessment scheme based on an improved PageRank algorithm for ranking notaries. Addressing the distinct roles undertaken by notaries of varying levels in cross-chain transactions, differentiated reputation evaluation strategies are developed for junior and intermediate notaries to ensure fairness and rationality in the reputation assessment process. Through this algorithm, the system can dynamically adjust the reputation rankings of notaries, effectively enhancing the trustworthiness and security of the cross-chain transaction system.

The remainder of this paper is structured as follows. Section II discusses recently proposed cross-chain interoperability schemes. Section III provides a detailed description of the scheme proposed in this paper. Section IV compares the performance of the scheme proposed in this paper with that of other schemes and provides its security analysis. Finally, Section V concludes this paper.

## II. Related Works

In recent years, based on the four commonly recognized cross-chain technologies, various cross-chain transaction schemes [16], have been successively proposed. Enhancing cross-chain technology requires addressing multiple challenges, including system reliability [17], scalability [18], performance [19], and security [20].

Hou et al. [21] and Wang et al. [22], employed relay chains as communication bridges to enable cross-chain transactions, reducing the integration costs of heterogeneous blockchains and improving the performance of cross-chain systems; however, the protection of cross-chain data still offers room for optimization. Wu et al. [23], introduced an encryption scheme based on smart contracts, establishing constrained relationships between relay chains and other blockchains to enhance system security and privacy protection. Furthermore, Wang et al. [24], enhanced the scalability of relay chain-based cross-chain systems through sharding operations applied to the relay chain. Nevertheless, the application of existing relay chain technologies in cross-chain transactions continues to face challenges, including implementation complexities, suboptimal performance, and inadequate system stability [25].

Li et al. [26], integrated Hash Time-Locked Contract (HTLC) with a virtual account verification mechanism, thereby improving the success rate of cross-chain transactions. Wang et al. [27], incorporated a dynamic premium adjustment mechanism and a credit mechanism into HTLC, proposing a Hash Time Lock with Dynamic Premium Based on Credit in Cross-Chain Transaction to address issues of transaction default and reduced efficiency in cross-chain transactions. Yu et al. [28], applied an optimized HTLC to a Multi-Agent System, enhancing security and transparency. However, when handling complex, high-value transactions, HTLC continues to exhibit significant limitations in scalability and transaction efficiency [29].

Yu et al. [30], proposed a key management scheme based on distributed identity, mitigating the pervasive issue of trust centralization in cross-chain transactions. Zhao et al. [31], further leveraged distributed private key technology to eliminate reliance on trusted nodes, thereby safeguarding the interests of participants in secret-sharing protocols and avoiding the risk of single-point failures. Ren et al. [32], integrated distributed keys with a Proof of Trust Contribution consensus algorithm and a non-interactive zero-knowledge proof protocol, enhancing both the efficiency of key generation and the security of key management. However, as the number of nodes increases, distributed private key control technology faces the challenge of balancing computational efficiency with system security.

Compared to the other three cross-chain schemes, the notary mechanism offers advantages such as low implementation cost, rapid transaction processing speed, and support for cross-chain transactions across multiple blockchains, proving particularly efficient in trusted environments. The Interledger Protocol [33], proposed by Ripple Labs, focuses on enabling cross-chain payments through a universal framework and serves as a quintessential example of the notary mechanism. However, its conflict with the core decentralized ethos of blockchain technology raises significant security concerns. Xiong et al. [34], introduced a notary committee comprising multiple notaries, selecting notaries based on reputation to handle cross-chain transactions, thereby eliminating dependence on a single notary and enhancing the system's resilience against malicious notaries. Nevertheless, the comprehensiveness of notary reputation assessment remains inadequate. To address this issue, Chen et al. [35], proposed a dynamic reputation management scheme based on the past transaction behavior of nodes. This scheme designs reputation evaluation metrics by analyzing prevalent security threats and incorporates a Particle Swarm Optimization algorithm to dynamically adjust metric weights, enabling adaptation to varying frequencies of malicious behavior. However, as it considers only common blockchain security threats, the scheme exhibits limitations in specific cross-chain scenarios.

Addressing the strengths and weaknesses of existing cross-chain schemes, this paper proposes the HMNG-CCM. This mechanism categorizes the notary group into three levels—junior notaries, intermediate notaries, and senior notaries—based on reputation, aiming to optimize the notary election process and reduce the system's centralization. Concurrently, it designates that only intermediate and junior notaries are responsible for transaction execution, while senior notaries are exclusively tasked with transaction verification, further refining the cross-chain transaction process. Additionally, differentiated reputation evaluation strategies are established for junior and intermediate notaries, and an improved PageRank algorithm is introduced to dynamically adjust the reputation of notary nodes, ensuring the fairness and rationality of the assessment.

## III. Proposed Scheme

In this section, the architecture and operational principles of the HMNG-CCM are elaborated in detail. Through a

comprehensive cross-chain protocol (preparation phase, transaction phase, and confirmation phase), this study designs and implements a cross-chain model based on notary group, an improved PageRank algorithm, a hierarchical management scheme of the notary group, and a hierarchical notary election process.

### A. Cross-Chain Model Based on Notary Group

The cross-chain model based on a hierarchically managed notary group proposed in this paper ensures the security of cross-chain interoperability by introducing a notary group and subjecting it to hierarchical management. As illustrated in Fig. 1, the system comprises three key components: the notary group, the source chain, and the target chain.

*1) Notary group:* This component consists of multiple nodes, each possessing at least one account on both the source chain and the target chain. During the initialization of the notary group, the system leverages smart contracts to create two margin pool accounts—one on the source chain and one on the target chain—and generates a set of notary nodes. The reputation of each node is calculated using an improved PageRank algorithm, and based on these reputation rankings, nodes are classified into junior notaries, intermediate notaries, and senior notaries, thereby establishing and maintaining the management framework of the notary group.

*2) Source chain:* This component refers to the blockchain where the sender of a cross-chain transaction resides. During the cross-chain transaction process, the primary participants on the source chain include the sender node, notary nodes, and the margin pool account maintained by the notary group on the source chain.

*3) Target chain:* This component refers to the blockchain where the receiver of a cross-chain transaction resides. During the cross-chain transaction process, the primary participants on the target chain include the receiver node, notary nodes, and the margin pool account maintained by the notary group on the target chain.

### B. Reputation Evaluation Scheme Based on an Improved PageRank Algorithm

The PageRank algorithm is a link analysis-based webpage ranking method designed to evaluate the relative importance of webpages within a hyperlinked network. Its fundamental expression is given as follows:

$$PR(A) = \frac{1-d}{N} + d \cdot \sum_{i \in M(A)} \frac{PR(j)}{L(j)} \quad (1)$$

In Eq. (1), $PR(A)$ represents the PageRank value of webpage $A$, $M(A)$ represents the set of webpages linking to webpage $A$, $L(j)$ indicates the number of outbound links from webpage $j$, $N$ signifies the total number of webpages, and $d$ is the damping factor, which models the random navigation behavior of users between webpages. This algorithm iteratively computes values until convergence, yielding the importance ranking of each webpage.

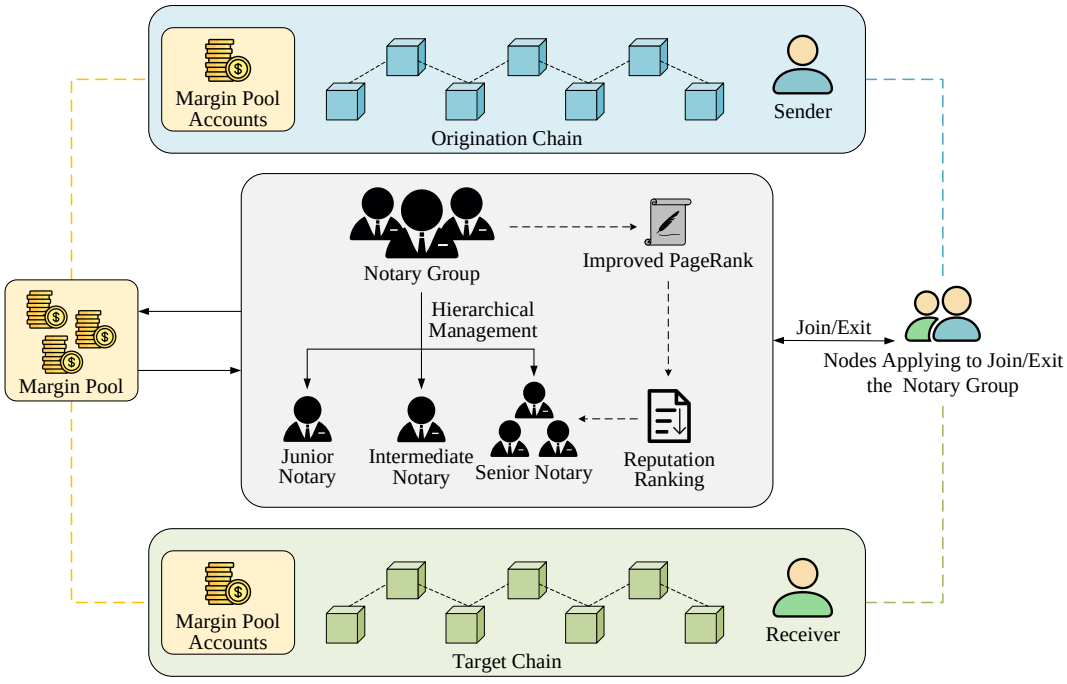



Fig. 1. Cross-chain model based on notary group.

Intermediate notaries primarily assess the comprehensive reputation of their nodes by incorporating the historical transaction success rate, transaction processing efficiency, and margin of the nodes. Table I presents the attributes of each parameter for intermediate notaries.

TABLE I. LIST OF INTERMEDIATE NOTARY PARAMETER ATTRIBUTES

| Reputation Metrics | Parameter Name | Weight |
|---|---|---|
| Trust Relationships | *PR(j)/L(j)* | 0.5 |
| Historical Transaction Success Rate | *HTSR* | 0.2 |
| Transaction Processing Efficiency | *TPE* | 0.2 |
| Margin | *M* | 0.1 |

Two assumptions are presented here:

*1) Quantity assumption:* It is assumed that a notary node exists, and if a substantial number of other notary nodes establish trust relationships with it, this indicates that the notary node possesses a high reputation.

*2) Quality assumption:* It is assumed that a notary node exists, and if another notary node with a high reputation establishes a trust relationship with it, the former notary node will be conferred a correspondingly high reputation.

$PR(j)/L(j)$ reflects the degree of trust that other nodes place in the given notary node. If a trust relationship exists between two nodes, they can mutually transfer reputation. Based on Quantity Assumption and Quality Assumption, it follows that the more trust relationships a notary node possesses, the greater the reputation transferred to it, resulting in a higher reputation for that node. $PR(j)/L(j)$ is a critical factor in the proposed reputation assessment scheme and is therefore assigned a weight of 0.5 as a foundational parameter.

$HTSR$ is utilized to measure the proportion of transactions successfully completed by a notary node among those in which it participates, thereby reflecting the node's transaction success rate. Consequently, $HTSR$ is assigned a weight of 0.2.

$$HTSR = \frac{Success - Fail}{Success + Fail + \varphi} \tag{2}$$

In Eq. (2), *Success* represents the number of successful transactions among those in which the notary node participates, $Fail$ denotes the number of failed transactions, and $\varphi$ is a very small constant.

$TPE$ is primarily employed to evaluate the transaction processing capability of a notary node. A shorter transaction time indicates greater efficiency of the node in processing transactions. Its weight is set at 0.2.

$$TPE = \frac{1}{n}\sum_{k=1}^{n}\frac{1}{t_k} \tag{3}$$

In Eq. (3), $t_k$ represents the time cost for the notary node to successfully complete the $k$-th transaction, while $n$ denotes the total number of transactions that the notary node has successfully completed.

The margin parameter $M$ reflects the amount of the deposit paid by a notary node upon joining the notary group. A higher margin corresponds to greater losses for the node in the event of malicious behavior. The weight of $M$ is set at 0.1.

$$M(i) = \frac{M_i - M_{\min}}{M_{\max} - M_{\min}} \tag{4}$$

In Eq. (4), $M_{\max}$ represents the maximum margin amount among all current nodes, $M_{\min}$ denotes the minimum margin amount, and $M(i)$ signifies the normalized result of the margin amount paid by node $i$.

The improved PageRank algorithm is presented in Eq. (5):

$$PR(i) = \frac{1-d}{N} + d \cdot [0.5 \sum_{j \in M(i)} \frac{PR(j)}{L(j)} + 0.2HTSR(i) + 0.2TPE(i) + 0.1M(i)] \tag{5}$$

In Eq. (5), $PR(i)$ represents the reputation of node $i$, $N$ denotes the total number of notary nodes, and $d$ is the damping factor, set at 0.85. $PR(j)$ indicates the reputation of node $j$, while $L(j)$ signifies the number of nodes evaluated by node $j$.

The reputation evaluation strategy for junior notaries incorporates not only the node's historical transaction success rate, transaction processing efficiency, and margin, but also the time a node waits to become a transaction notary. Table II lists the attributes of each parameter for junior notaries.

TABLE II. LIST OF JUNIOR NOTARY PARAMETER ATTRIBUTES

| Reputation Metrics | Parameter Name | Weight |
|---|---|---|
| Trust Relationships | *PR(j)/L(j)* | 0.4 |
| Historical Transaction Success Rate | *HTSR* | 0.2 |
| Transaction Processing Efficiency | *TPE* | 0.2 |
| Margin | *M* | 0.1 |
| Waiting Time | *T* | 0.1 |

Similarly, in calculating the reputation of junior notaries, the weight of $PR(j)/L(j)$ is set to 0.4, the weight of $HTSR$ is set to 0.2, the weight of $TPE$ is set to 0.2, and the weight of $M$ is set to 0.1. Additionally, the parameter $T$, representing the waiting time, is introduced in the reputation calculation for junior notaries, with its weight set to 0.1.

The parameter $T$ is employed to measure the waiting time of a notary node before it becomes a transaction notary. For junior notaries, the opportunities to be selected as transaction notaries and participate in transactions are limited, resulting in longer waiting times. The introduction of parameter $T$ provides junior notaries, who have been part of the notary group for an extended period but lack transaction participation

opportunities, with a prioritized opportunity to advance to intermediate notaries. Simultaneously, it increases the time cost for newly joined malicious nodes within the notary group, reducing the likelihood of such nodes being elected as transaction notaries, thereby enhancing the security of cross-chain operations.

$$T(i)=\frac{T_i - T_{\min}}{T_{\max} - T_{\min}} \tag{6}$$

In Eq. (6), $T_{\max}$ represents the maximum waiting time among all current nodes to become a transaction notary, $T_{\min}$ denotes the minimum waiting time, and $T(i)$ signifies the normalized result of the waiting time for node $i$.

The improved PageRank algorithm is presented in Eq. (7):

$$PR(i)=\frac{1-d}{N}+d\cdot[0.4\sum_{j\in M(i)}\frac{PR(j)}{L(j)} +0.2HTSR(i)+0.2TPE(i)+0.1M(i)+0.1T(i)] \tag{7}$$

In Eq. (7), $PR(i)$ represents the reputation of node $i$, $N$ denotes the total number of notary nodes, and $d$ is the damping factor, set at 0.85. $PR(j)$ indicates the reputation of node $j$, while $L(j)$ signifies the number of nodes evaluated by node $j$.

### C. Hierarchical Management Scheme of the Notary Group

The notary group, based on reputation rankings, employs a normal distribution to classify notary nodes into three levels, as illustrated in Fig. 2: junior notaries, intermediate notaries, and senior notaries.

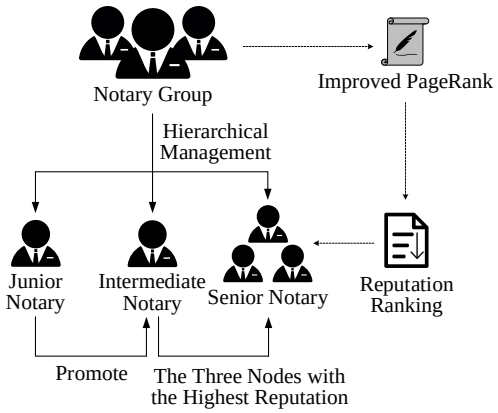



Fig. 2. Hierarchical management scheme of the notary group.

Based on a normal distribution, notary nodes with a reputation less than -1σ are designated as junior notaries, representing the bottom 16% of the notary group in terms of reputation ranking. Notary nodes with a reputation greater than -1σ are classified as intermediate notaries, encompassing the top 84% of the notary group by reputation ranking. Senior notaries are selected as the three nodes with the highest reputation from among the intermediate notaries, corresponding to the three highest-ranked notaries in the entire notary group.

Within the notary group, transaction notaries are preferentially elected from intermediate notaries based on their reputation. Only when no intermediate notary meets the transaction requirements is the same method applied to elect from junior notaries. The promotion of a junior notary to an intermediate notary is contingent upon its reputation. The reputation calculation for junior notaries differs from that of intermediate notaries, notably incorporating the waiting time to become a transaction notary as a significant factor in the evaluation. By appropriately assigning weights, junior notaries with longer waiting times and otherwise favorable attributes achieve higher reputation scores, thereby gaining priority for promotion to intermediate notaries and increasing their opportunities to participate in transactions. The verification of cross-chain transactions is exclusively handled by senior notaries, specifically the three nodes with the highest reputation in the entire notary group, who collectively perform validation through multi-signature processes. Funds are released only after at least two senior notaries have completed their signatures.

### D. Hierarchical Notary Election

The hierarchical notary election process is depicted in Fig. 3.

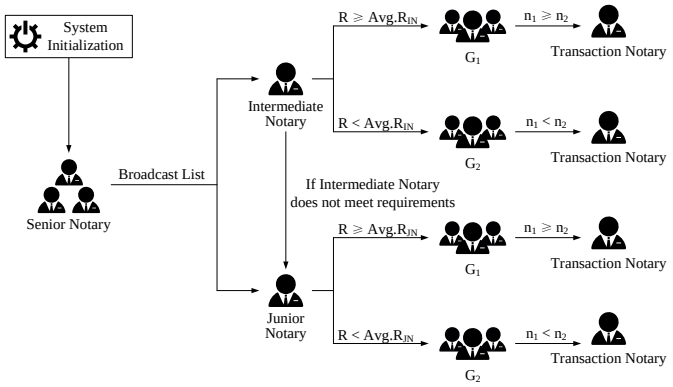



Fig. 3. Hierarchical notary election.

Initially, during the notary initialization phase, the system categorizes each notary into junior notaries, intermediate notaries, and senior notaries based on their reputation. In the preparation stage of a cross-chain transaction, senior notaries broadcast the transaction list within the notary group, detailing the key attributes of the transactions. Each notary then determines whether to participate in the notary election based on the transaction details. Subsequently, the system calculates the average reputation of the intermediate notaries and, based on this mean value, divides them into two groups: $G_1$, consisting of notaries with a reputation greater than or equal to the average, and $G_2$, comprising notaries with a reputation below the average. The number of notaries in $G_1$ is denoted as $n_1$, and in $G_2$ as $n_2$. If $n_1 \geq n_2$, a notary meeting the transaction requirements is elected from $G_1$ as the transaction notary; otherwise, the same method is applied to elect a

transaction notary from $G_2$. Should no intermediate notary fulfill the transaction requirements, the system employs the same approach to conduct the election among junior notaries. The specific procedure is outlined in Algorithm 1.

**Algorithm 1:** Notary Election

**Input:** $List_{TRA}$, $Tab_R$, $IN$, $JN$

**Output:** $TN$

```
function ELECTION( List_TRA , Tab_R , IN , JN )
  Broadcast( List_TRA )
  R ← DeleteZeroReputationNotary( Tab_R )
  TN ← Elect( IN )
  Avg.R ← Average( R )
  G_1 ← GetIN( R ≥ Avg.R ), n_1 = Count( G_1 )
  G_2 ← GetIN( R < Avg.R ), n_2 = Count( G_2 )
  if n_1 ≥ n_2 then
    TN ← Random( G_1 )
  else if n_1 < n_2 then
    TN ← Random( G_2 )
  else if TN ← Null( IN ) then
    return Elect( JN )
  end if
  return TN
end function
```

## IV. Performance Analysis

The simulation experimental environment for this scheme is executed on a laptop equipped with the Windows 11 operating system, featuring hardware specifications that include a 13th-generation Intel(R) Core(TM) i5-13500H 2.60 GHz processor and 16 GB RAM. The blockchain system is constructed within a virtual machine running Ubuntu 24.04 Desktop Edition, configured with a 4-core processor and 8 GB RAM. The blockchain system utilized in the experiments is based on Hyperledger Fabric 2.4, comprising two independent blockchains with identical configurations.

### A. Election Performance of the Improved PageRank Algorithm

This experiment constructs a notary group comprising 50 nodes. During initialization, each node is assigned a uniform initial reputation of 0.02 and numbered from 1 to 50. Nodes numbered 1 to 3 are preconfigured with a higher density of trust relationships and are designated as senior notary nodes in the HMNG-CCM framework; nodes numbered 4 to 42 are configured with baseline trust relationships and defined as intermediate notary nodes; and newly added nodes numbered 43 to 50, lacking pre-established trust relationships, are classified as junior notary nodes. Throughout the iteration process, the establishment of trust relationships is determined by the current reputation of each node, with the probability of a node gaining new trust relationships being positively correlated with its current reputation. The iteration concludes when the reputation of each node stabilizes, with the resulting reputation values for each node presented in Fig. 4.

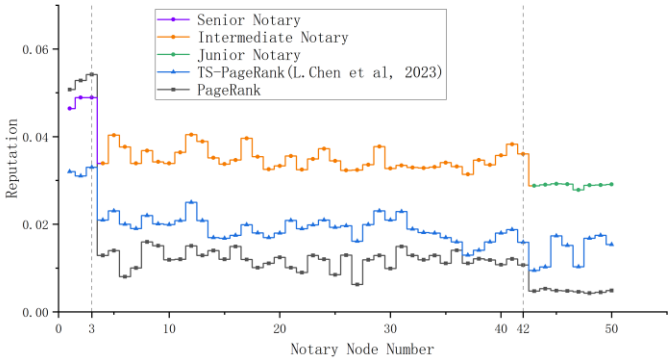



Fig. 4. Results of the PageRank, TS-PageRank, and HMNG-PageRank.

The original PageRank algorithm, due to its excessive reliance on trust relationships, results in nodes numbered 1 to 3 (mean: 0.052) exhibiting significantly higher reputation scores than nodes numbered 4 to 42 (mean: 0.012) and nodes numbered 43 to 50 (mean: 0.0048). This approach overlooks the complexity of notary reputation evaluation in cross-chain transactions, leading to a one-sided assessment of reputation. In contrast, the TS-PageRank [36] algorithm, when computing the reputation of notary nodes, incorporates parameters that may influence node reputation in cross-chain transactions, partially mitigating the short-comings of the original PageRank algorithm. However, it demonstrates insufficient differentiation between nodes numbered 4 to 42 and those numbered 43 to 50, which may result in the erroneous election of newly joined malicious nodes as transaction notaries during the notary selection process, consequently reducing system security.

HMNG-CCM designs differentiated reputation evaluation strategies for junior and intermediate notaries. Consequently, the reputation of senior, intermediate, and junior notaries, computed via the improved HMNG-PageRank algorithm, exhibits a discernible level of differentiation while achieving a smooth transition from senior to junior levels. This approach avoids the steep drop-off observed in the original PageRank algorithm and the flat distribution of the TS-PageRank algorithm, ensuring a comprehensive reputation assessment. Furthermore, the differentiated evaluation strategy demonstrates a high degree of adaptability to the hierarchical requirements of notary elections, whereas the original PageRank and TS-PageRank algorithms, lacking similar designs, exhibit limitations under complex trust relationship scenarios.

In summary, the HMNG-PageRank algorithm excels in reputation evaluation within the notary group. Compared to the original PageRank and TS-PageRank, this scheme offers superior reliability and security, providing robust support for the hierarchical notary election mechanism.

### B. Comparison of Notary System Time Cost and Cross-Chain Transaction Time

This experiment analyzes the time cost of each phase in cross-chain transactions, testing the average time costs of the

preparation phase, transaction phase, confirmation phase, and notary system under scenarios involving the simultaneous initiation of 20, 40, 60, 80, 100, and 120 transactions. The experimental results are presented in Fig. 5. The preparation phase accounts for approximately 37.1% of the total time cost in the cross-chain transaction process, the transaction phase constitutes about 47.5%, and the confirmation phase comprises roughly 15.4%. The time cost of the notary system, which forms a subset of the preparation phase, represents approximately 4.5% of the total time cost. The proportion of time attributed to the notary system is significantly lower than that of the entire cross-chain transaction process, indicating that the additional time overhead introduced by the notary management scheme is negligible. Furthermore, as the number of transactions increases from 20 to 120, the average cross-chain transaction time rises by only 4.6%, demonstrating the efficiency of HMNG-CCM in resource allocation and its adaptability to varying transaction scales.

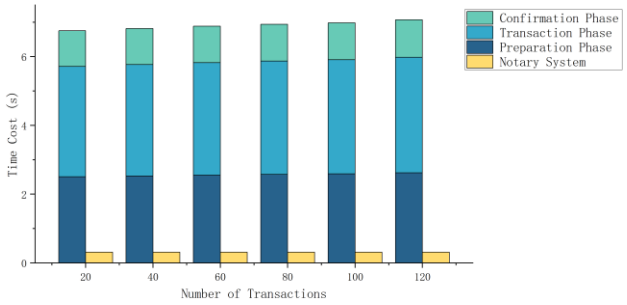



Fig. 5. Notary system time cost and cross-chain transaction time.

### C. Impact of Malicious Nodes on Cross-Chain Transaction Time

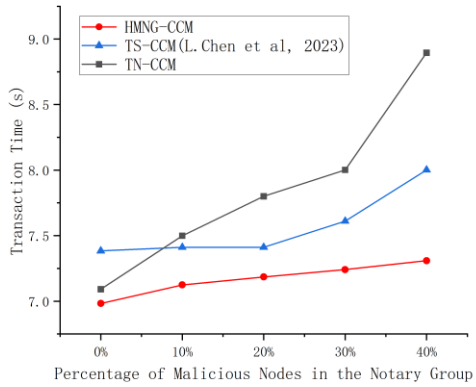
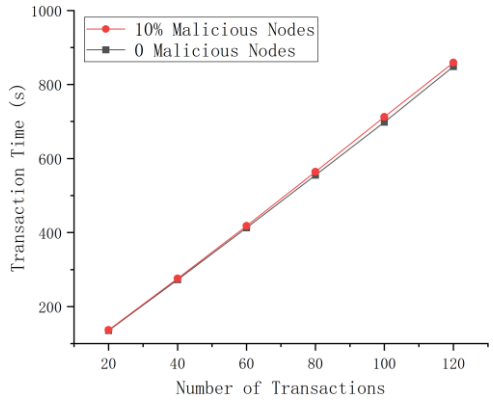



Fig. 6. Transaction time under different percentages of malicious nodes.

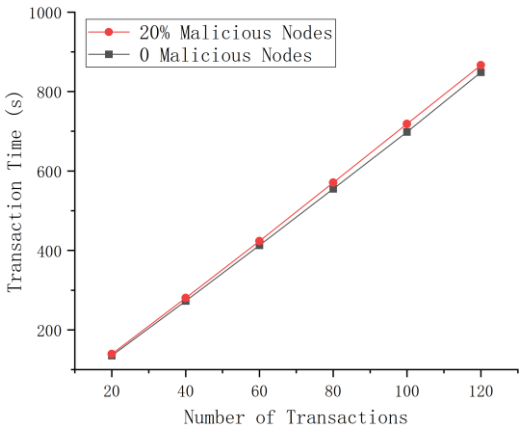
This experiment initiates 100 transaction requests to evaluate cross-chain transaction times when the notary group contains 0, 10%, 20%, 30%, and 40% malicious nodes. The experimental results are presented in Fig. 6. The Traditional Notary Cross-Chain Mechanism (TN-CCM) exhibits low tolerance to malicious nodes. As the proportion of malicious nodes increases, the cross-chain transaction time consistently rises. Notably, when the proportion of malicious nodes exceeds 30%, the transaction time surges to 8.9 seconds, representing a time cost increase of approximately 25.4%, which indicates a marked degradation in system performance.

The Three-Stage Cross-Chain Mechanism (TS-CCM) [36], operates normally when the proportion of malicious nodes remains below 20%, with transaction times stabilized at approximately 7.4 seconds. However, when the proportion of malicious nodes exceeds 20%, transaction time increase sharply to 8 seconds, resulting in an approximate time cost rise of 8.4%, with further escalation as the proportion of malicious nodes continues to grow. This indicates that TS-CCM experiences significant impacts on its performance and stability when confronted with higher proportions of malicious nodes.

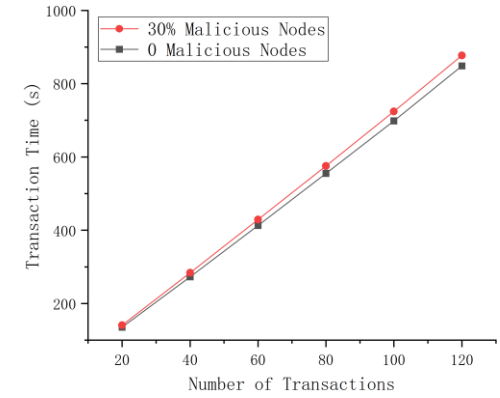
Throughout the range of 0% to 40% malicious nodes, HMNG-CCM consistently demonstrates lower cross-chain transaction times compared to TN-CCM and TS-CCM. Moreover, as the proportion of malicious nodes increases, the growth in transaction time for HMNG-CCM remains relatively minor. Specifically, when the proportion of malicious nodes reaches 40%, the transaction time increases by only 4.67%, demonstrating its robustness and resistance to malicious behavior. In summary, the experimental results comprehensively validate that HMNG-CCM not only maintains high efficiency when the proportion of malicious nodes is low, but also sustains stable system performance under scenarios with a high proportion of malicious nodes. This reflects the significant engineering value of HMNG-CCM in enhancing the efficiency and reliability of cross-chain transactions.



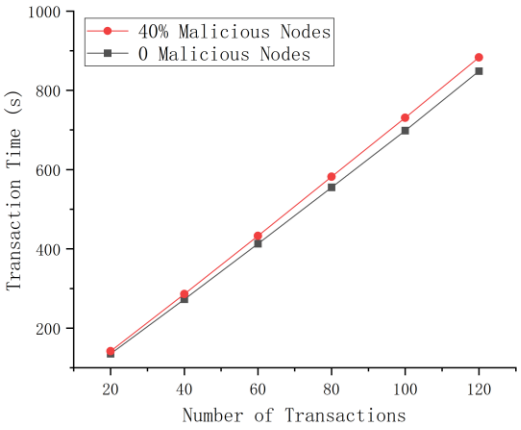

(a) 10% Malicious Nodes




(b) 20% Malicious Nodes




(c) 30% Malicious Nodes




(d) 40% Malicious Nodes

Fig. 7. Impact of different percentages of malicious nodes on transaction time under different numbers of transactions.

This experiment evaluates the performance of HMNG-CCM in counteracting malicious notary nodes during cross-chain transactions. The experiment simulates five scenarios with malicious notary proportions of 0% (control group), 10%, 20%, 30%, and 40%. For each scenario, 20, 40, 60, 80, 100, and 120 transactions are processed, analyzing the impact of both transaction volume and malicious notary proportion on transaction time. The experimental results are presented in Fig. 7. In the absence of malicious nodes (0%), cross-chain transaction times are the shortest, exhibiting linear growth with increasing transaction volume. As the proportion of malicious nodes rises from 10% to 40%, transaction time increases slightly compared to the 0% malicious notary scenario, as evidenced by the gradually widening vertical distance between the corresponding line segments and the 0% malicious notary baseline in the figure. Nevertheless, even when the malicious notary proportion reaches 40%, transaction times remain closely aligned with those in the 0% scenario. This demonstrates that HMNG-CCM sustains robust performance even under high proportions of malicious nodes. Furthermore, regardless of the increase in transaction volume, the influence of varying malicious notary proportions on transaction time remains limited, highlighting the efficiency and robustness of HMNG-CCM in mitigating interference from malicious nodes.

### D. Impact of Malicious Nodes on Transaction Success Rate

This experiment initiates 100 transaction requests to assess the cross-chain transaction success rate under scenarios where the notary group contains malicious nodes at proportions of 10%, 20%, 30%, and 40%. The experimental results are presented in Fig. 8. TN-CCM exhibits low tolerance to malicious behavior; as the proportion of malicious nodes increases, the transaction success rate declines linearly from 100% to 60%. This indicates that TN-CCM struggles to maintain normal system operation effectively when the proportion of malicious nodes is high. TS-CCM [36], performs stably when the malicious notary proportion is below 30%, maintaining a transaction success rate of 98%. However, when the proportion exceeds 30%, the success rate drops sharply to 88%, highlighting its limited resilience against malicious behavior in high-risk scenarios.

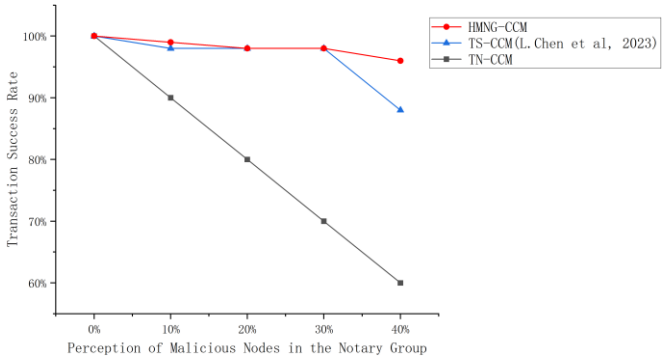



Fig. 8. Transaction success rate under different percentages of malicious nodes.

In contrast, HMNG-CCM achieves a transaction success rate of 99% when the malicious notary proportion is below 20%, slightly outperforming TS-CCM. Between 20% and 30%, the success rate remains stable at 98%. Even when the malicious notary proportion reaches 40%, HMNG-CCM sustains a success rate of 96%, with a mere 4% decline, markedly surpassing both TN-CCM and TS-CCM. These results demonstrate that HMNG-CCM effectively ensures transaction success rates in scenarios with high proportions of malicious nodes, reflecting superior system reliability and robustness under complex scenarios.

### E. Security Analysis

The notary-based cross-chain transaction system may encounter threats such as malicious notary attacks, single points of failure, and reputation manipulation. The HMNG-CCM proposed in this paper effectively addresses these potential threats and ensures system robustness and reliability through an innovative hierarchical notary management scheme, a functional division mechanism, and a reputation evaluation mechanism based on an improved PageRank algorithm.

The core of HMNG-CCM lies in mitigating trust risks and enhancing system stability through hierarchical management and functional division. Notaries are classified into three tiers—junior, intermediate, and senior. Nodes newly joining the notary group must stake a margin deposit and undergo

verification by senior notaries to become junior notaries, while senior notaries are designated as the nodes with the highest reputation. This hierarchical structure circumvents the centralization risks inherent in traditional notary mechanisms due to reliance on a single notary. The synergy between functional division and hierarchical management enhances the system's decentralization. Transaction execution and verification duties are distinctly separated: junior and intermediate notaries handle the execution of cross-chain transactions, whereas senior notaries focus on verifying the legality and consistency of transactions. This division further diminishes the influence of any single notary on the system, while enabling the timely detection and correction of malicious behavior through multiple checks. Consequently, the system maintains normal operation even in the presence of partial node failures or attacks.

The reputation evaluation employs an improved PageRank algorithm, generating reputation rankings based on nodes' historical performance and trust relationships. Differentiated evaluation strategies are designed for junior and intermediate notaries to reflect their distinct role characteristics in transaction execution. Periodically updated reputation rankings effectively identify and isolate malicious nodes, ensuring that only those with a high reputation participate in critical tasks. This dynamic adjustment capability not only prevents reputation manipulation but also provides a fair basis for notary election and promotion. When junior notaries are considered for promotion to intermediate notaries, both historical performance and waiting time are comprehensively evaluated, offering priority promotion opportunities to junior notary nodes that have been part of the notary group for an extended period yet lack election opportunities. Simultaneously, this approach increases the time cost for newly joined malicious nodes within the notary group, reducing the likelihood of their election as selected notaries and thereby further mitigating their impact on the system.

Based on the aforementioned design, this scheme ensures transaction security and smooth execution through a cross-chain protocol. During the preparation phase, the system selects transaction notaries from intermediate or junior notaries based on reputation. In the transaction phase, senior notaries verify transactions via multi-signature validation and authorize transaction notaries to release funds, a decentralized verification approach that effectively prevents single points of failure. Furthermore, the system incorporates timeout and retry mechanisms to bolster risk resilience and employs distributed storage technology in the confirmation phase to safeguard transaction data security. Collectively, these design elements establish a secure and reliable transaction process.

## V. Conclusion

The HMNG-CCM proposed in this paper provides a decentralized, efficient, and trustworthy solution for blockchain cross-chain transactions by introducing an innovative notary management scheme, a functional division mechanism, and a reliable reputation evaluation mechanism.

Firstly, a notary management scheme centered on hierarchical management and functional division effectively mitigates trust risks and optimizes transaction processes, thereby enhancing the decentralization characteristics of the cross-chain system. Secondly, a reputation evaluation scheme designed using an improved PageRank algorithm implements differentiated assessments based on notary levels, ensuring fairness and rationality in the evaluation process. Furthermore, experimental results conducted on the Hyperledger Fabric platform demonstrate that this mechanism effectively withstands malicious notary behavior while improving transaction speed and success rate, confirming its advantages in practical applications.

Although this study has achieved significant progress, several limitations warrant further attention. The experimental validation is primarily based on the Hyperledger Fabric platform, and the generalizability of the results requires additional verification across other blockchain platforms. The hierarchical management scheme may increase management complexity when the number of notaries is large. Furthermore, the effectiveness and stability of the reputation evaluation scheme under diverse scenarios necessitate further testing.

Based on the findings and limitations of this study, future research could explore adaptive dynamic management schemes for notary groups, incorporate machine learning techniques to develop more flexible reputation evaluation models, and design cross-chain protocols that support multi-chain environments to accommodate increasingly complex blockchain interaction scenarios.

In conclusion, this paper successfully establishes an efficient and secure cross-chain mechanism, offering robust technical support for the security and decentralization of blockchain cross-chain transactions. While certain limitations remain, this study provides directions for future related research, bearing significant theoretical importance and practical value.

## Acknowledgment

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# Comprehensive Vulnerability Analysis of Three-Factor Authentication Protocols in Internet of Things-Enabled Healthcare Systems

Haewon Byeon
Department of Future Technology, Korea University of Technology and Education (Korea Tech),
Cheonan 31253, South Korea

***Abstract*—This study evaluates a three-factor authentication protocol designed for IoT healthcare systems, identifying several key vulnerabilities that could compromise its security. The analysis reveals weaknesses in single-factor authentication, time synchronization, side-channel attacks, and replay attacks. To address these vulnerabilities, the study proposes a series of enhancements, including the implementation of multi-factor authentication (MFA) to strengthen user verification processes and the inclusion of timestamps or nonces in messages to prevent replay attacks. Additionally, the adoption of advanced cryptographic techniques, such as masking and shuffling, can mitigate side-channel attacks by minimizing information leakage during encryption. The use of message authentication codes (MACs) ensures communication integrity by verifying message authenticity. These improvements aim to fortify the protocol's security framework, ensuring the protection of sensitive medical data. Future research directions include exploring adaptive security policies leveraging artificial intelligence and optimizing cryptographic operations to enhance efficiency. These efforts are essential for maintaining the protocol's resilience against evolving threats and ensuring the secure operation of IoT-based healthcare systems.**

***Keywords*—Three-factor authentication; IoT healthcare security; multi-factor authentication; side-channel attack mitigation; replay attack prevention**

## I. Introduction

The advent of the Internet of Things (IoT) has revolutionized numerous sectors, with healthcare emerging as one of the most transformative fields. IoT-enabled healthcare systems, commonly referred to as the Internet of Medical Things (IoMT), leverage interconnected medical devices to facilitate real-time monitoring, data collection, and analysis [1]. These systems enhance patient care by enabling continuous health monitoring, remote diagnosis, and timely medical interventions. However, the integration of IoT in healthcare also introduces significant security challenges, particularly concerning the protection of sensitive patient data from unauthorized access and cyber threats [2].

In response to these challenges, robust authentication protocols are paramount to ensure that only authorized users and devices can access sensitive medical information. Traditional authentication methods, often based on single or dual factors, have proven inadequate in the face of sophisticated cyber-attacks [3]. Consequently, three-factor authentication protocols have gained prominence as a more secure alternative [4]. These protocols typically combine knowledge-based (e.g., passwords), possession-based (e.g., smart cards), and inherence-based (e.g., biometric data) factors to provide a comprehensive security framework [4].

Despite their enhanced security, three-factor authentication protocols in IoT healthcare systems must address several challenges. The resource-constrained nature of many IoT devices limits their ability to execute complex cryptographic operations, necessitating the development of efficient, lightweight protocols [5]. Additionally, the dynamic and distributed nature of IoT networks requires authentication systems to be adaptable, maintaining security even as devices frequently join and leave the network [6]. Furthermore, ensuring user privacy and compliance with stringent healthcare regulations, such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR), is critical [7].

This research aims to conduct a comprehensive analysis of an efficient three-factor authentication protocol designed for IoT healthcare systems [5]. The primary objective is to identify and scrutinize four key security vulnerabilities within the protocol that could compromise its effectiveness. By examining the protocol's architecture and operational phases, this study seeks to uncover potential weaknesses and propose strategies for enhancement.

The paper is structured as follows: Section II presents a literature review of existing authentication protocols and their limitations. Section III outlines the methodology employed for vulnerability detection, including the analytical methods and tools used for cryptanalysis and security testing. Section IV discusses the identified vulnerabilities in detail, and proposes improvements to enhance the protocol's security and efficiency. Finally, Section V concludes with a summary of the findings and their implications for IoT-based healthcare authentication systems.

## II. Literature Review

### A. Current Authentication Protocols

The integration of the Internet of Things (IoT) into healthcare has necessitated the development of robust authentication protocols to protect sensitive medical data. Three-factor authentication schemes have gained prominence in

this context due to their enhanced security capabilities (Fig. 1). These protocols typically combine knowledge-based (e.g., passwords), possession-based (e.g., smart cards), and inherence-based (e.g., biometric features) factors to create a layered security framework [8].

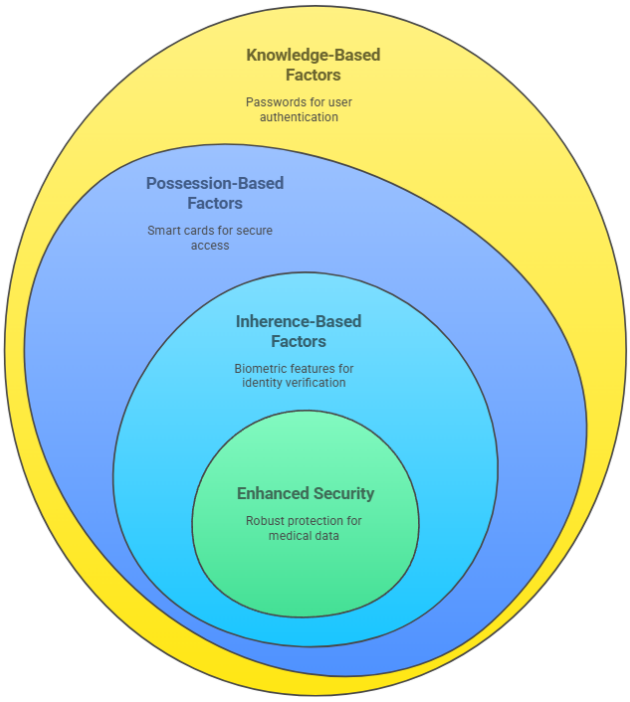


Fig. 1. Three-factor authentication in IoT healthcare security.

Despite their strengths, three-factor authentication protocols face significant challenges in IoT environments. The resource-constrained nature of many IoT devices limits their ability to execute complex cryptographic operations, necessitating the development of efficient, lightweight protocols [9]. Additionally, the dynamic and distributed nature of IoT networks requires authentication systems to be adaptable, maintaining security even as devices frequently join and leave the network [10].

Recent advancements in three-factor authentication protocols have focused on enhancing security while minimizing resource consumption. For instance, some protocols leverage elliptic curve cryptography (ECC) to provide strong security with reduced computational overhead [11]. Others incorporate advanced biometric recognition techniques, such as iris scanning, to enhance user authentication without physical contact, addressing both security and usability concerns [12].

### B. Related Works

The literature on IoT-based healthcare authentication systems reveals various vulnerabilities that necessitate ongoing research and innovation. One significant area of concern is the risk of sensor capture attacks, where adversaries gain physical access to devices and extract sensitive information. To mitigate this risk, some studies have proposed the integration of Physical Unclonable Functions (PUFs) as an additional authentication factor, providing a hardware-based layer of security resistance to cloning and physical attacks [13].

Another critical issue is the vulnerability of smart cards to theft and information extraction. While smart cards play a crucial role in safeguarding authentication schemes, their susceptibility to loss and unauthorized access poses a significant risk [14]. Research efforts have focused on developing secure storage and transmission mechanisms to protect the data stored on smart cards and ensure the integrity of the authentication process [15].

The literature also highlights the importance of privacy-preserving techniques in enhancing the security of IoT-based healthcare systems. Techniques such as zero-knowledge proofs and ring signatures have been proposed to protect user privacy while maintaining the transparency and auditability benefits of blockchain-based authentication [16].

In summary, the literature underscores the potential of three- factor authentication protocols to enhance security in IoT healthcare systems. However, addressing the identified vulnerabilities and challenges is crucial for realizing their full potential. Continued research and innovation in this field will play a vital role in securing the future of digital healthcare [17].

## III. Methodology

### A. Framework for Analysis

The methodology for analyzing the proposed three-factor authentication protocol for IoT in healthcare systems [5] involves a comprehensive framework designed to identify and evaluate potential security vulnerabilities. This framework integrates theoretical analysis, mathematical modeling, and practical testing to ensure a thorough security assessment.

### B. Analytical Methods for Vulnerability Detection

The analysis begins with a structured examination of the protocol's architecture, focusing on its critical components: registration, authentication, and session key establishment. Formal security models and logical proofs are employed to assess the protocol's resilience against various attack vectors. One such method is the application of Burrows-Abadi-Needham (BAN) logic, which helps to verify the authenticity and freshness of messages exchanged within the protocol:

$$P \mid\equiv X \quad \text{(P believes X)}$$

$$P \mid\Rightarrow X \quad \text{(P has jurisdiction over X)}$$

$$(X) \quad \text{(X is fresh)}$$

These logical expressions formalize the assumptions made during the protocol's execution, ensuring that it meets its intended security objectives [5].

### C. Mathematical Modeling of Protocol Operations

The analysis incorporates mathematical modeling to evaluate key cryptographic operations, such as key generation and exchange. The protocol employs elliptic curve cryptography (ECC) for secure key exchanges:

$$K_{session} = g^{ab} \backslash \text{modp}$$

where, (g) is a generator point, and (a) and (b) are private keys of the communicating entities. This session key ensures secure communication between devices [5].

## IV. Analysis of the Proposed Protocol

### A. Overview of the Protocol

The proposed three-factor authentication protocol for IoT in healthcare systems is designed to enhance security through a series of robust cryptographic operations. The protocol is divided into several key phases: registration, authentication, and session key establishment. .

*1) Registration phase:* This phase initiates the secure setup of the system, where devices and users are registered with the central server. Each IoT device generates a random number $(a_i)$ and computes a pseudo-identity $(PID_i = h(ID_i \| a_i))$, where, $(h(\ ))$ is a secure hash function and $(ID_i)$ is the device's unique identifier (Fig. 2). The registration message sent to the server includes these parameters, ensuring that the device's identity is securely bound to its registration process [5].

| User $U_i$ | Gateway node $GW$ |
|---|---|
| Chooses $ID_i$, $PW_i$ and random number $r_i$<br>Also imprints $B_i$ at the sensor device<br>Computes $RPW_i = h(ID_i \| PW_i \| r_i)$,<br>$F_i = H(B_i \| r_i)$<br>$\xrightarrow{\{ID_i, RPW_i, F_i\}}$ | |
| | Produces a dynamic identity $DID_i$ and $R_g$<br>Calculates $A_i = h(DID_i \| X_G \| ID_g) \oplus h(RPW_i \| F_i)$,<br>$C_i = R_g \oplus h(DID_i \| X_G \| ID_g)$,<br>$D_i = h(RPW_i \| R_g \| F_i)$<br>Issue smartcard $\{A_i, C_i, D_i, DID_i, H(\cdot), h(\cdot)\}$<br>$\xleftarrow{Smartcard}$ |
| Compute $R_n = r_i \oplus h(ID_i \| PW_i \| H(B_i))$ and stores it into smartcard | |

Fig. 2. Overview of the protocol's user registration phase.

| User $U_i$ | Gateway node $GW$ | Sensor node $SN_j$ |
|---|---|---|
| | Computes $M_1 = M_1 \oplus h(DID_i \| X_G \| ID_g)$, $R_g = C_i \oplus h(DID_i \| X_G \| ID_g)$<br>Decrypts $M_2$ as $(ID_i \| SID_j \| T_1 \| A_i) = D_{h(M_1 \| R_g)}(M_2)$<br>If $T_2 - T_1 \leq \triangle T$ holds, Ok; Else quits.<br>Computes $h(RPW_i \| F_i) = A_i \oplus h(DID_i \| X_G \| ID_g)$,<br>$M'_3 = h(ID_i \| SID_j \| h(RPW_i \| F_i))$<br>If $M'_3 \stackrel{?}{=} M_3$ holds, Ok; Else quits.<br>Computes $X_{GS} = h(SID_i \| X_G)$,<br>$K_j = h(X_{GS} \| Y_G \| X_G)$.<br>$M_4 = E_{h(X_{GS} \| K_j)}(ID_g \| ID_i \| M_i \| A_i \| T_3)$,<br>$M_5 = N_i \oplus h(T_3 \| h(RPW_i \| F_i))$,<br>$M_6 = h(ID_i \| N_i \| T_3 \| ID_g)$<br>$\xrightarrow{\{M_1, M_4, M_5, M_6\}}$ | |
| | | Decrypts $M_4$ using $X_{GS}$ and $K_j$<br>As $(ID_g \| ID_i \| M_i \| A_i \| T_3) = D_{h(X_{GS} \| K_j)}(M_4)$<br>If $T_4 - T_3 \leq \triangle T$ holds, Ok; Else quits.<br>$h(RPW_i \| F_i) = M_1 \oplus M_i \oplus A_i$,<br>$N_i = h(T_3 \| h(RPW_i \| F_i)) \oplus M_5$.<br>$M'_6 = h(ID_i \| N_i \| T_3 \| ID_g)$<br>If $M'_6 \stackrel{?}{=} M_6$ holds, Ok; Else quits.<br>Calculates $M_7 = V_i \oplus h(M_i \| N_i)$,<br>$SK = h(h(RPW_i \| F_i) \| M_i \| N_i \| V_i))$,<br>$M_8 = h(SK \| ID_i \| ID_g \| T_5)$.<br>$\xleftarrow{\{M_7, M_8, T_5\}}$ |
| | Checks $T_6 - T_5 \leq \triangle T$.<br>Computes $T_i = M_7 \oplus h(M_i \| N_i)$, $SK' = h(h(RPW_i \| F_i) \| M_i \| N_i \| V_i))$,<br>$M'_8 = h(SK' \| ID_i \| ID_g \| T_5)$. $SN_j$<br>If $M'_8 \stackrel{?}{=} M_8$ holds, Ok; Else quits.<br>Computes $C_i^n = R_g \oplus h(DID_i^n \| X_G \| ID_g)$ and updates the database $\{DID_i^n, C_i^n\}$<br>Computes $M_9 = E_{h(RPW_i \| F_i)}(C_i^n \| N_i \| V_i \| DID_i^n)$ and $M_{10} = h(SK \| C_i^n \| DID_i^n)$.<br>$\xleftarrow{\{M_9, M_{10}\}}$ | |
| Decrypts $(C_i^n \| N_i \| V_i \| DID_i^n) = D_{h(RPW_i \| F_i)}(M_9)$, and computes $SK' = h(h(RPW_i \| F_i) \| M_i \| N_i \| V_i))$,<br>$M'_{10} = h(SK' \| C_i^n \| DID_i^n)$<br>If $M'_{10} \stackrel{?}{=} M'_{10}$ holds, replaces $DID_i$ with $DID_i^n$ and $C_i$ with $C_i^n$. | | |

Fig. 3. Overview of the protocol's user authentication phase.

*2) Authentication phase:* During this phase, mutual authentication between the IoT device and the central server is established. The protocol employs elliptic curve cryptography (ECC) for secure key exchanges (Fig. 3). Each device computes an authentication token using a hash of its identity and a session-specific random nonce:

$$\text{AuthToken} = h(ID_i \parallel \text{Nonce}_i)$$

This token is used to verify the device's authenticity, ensuring that only legitimate devices can participate in the network [5].

*3) Session key establishment:* Once authentication is successful, a secure session key is established between the device and the server. The session key ($K_{session}$) is derived from the ECC-based key exchange process:

$$K_{session} = g^{ab} \backslash \text{mod} p$$

where, ( g ) is a generator point on the elliptic curve, and ( a ) and ( b ) are private keys of the communicating entities. This ensures that each session is secured with a unique key, providing confidentiality and integrity for data exchanged between the device and the server [5].

### B. Identified Vulnerabilities

Off-line Password Guessing Attack:

- Problem: The protocol aims to prevent off-line password guessing attacks, but an attacker can leverage leaked information from the registration phase (e.g., Regi = h(IDi || R₁ || HPWi), Ai = R; ⊕ HPWi, Ci = Bi ⊕ h(IDi ⊕ R; ⊕ HPWi)) and perform an off-line attack. Given a compromised HPWi, an attacker can try to guess PWi* such that h(IDi ⊕ PWi*) == HPWi.
- Attack Success Probability: The probability of a successful off-line guessing attack, given a limited password space and number of guesses is:

P(success) ≈ 1 - (1 - 1/|Password Space|)^N

where, |Password Space| is the size of the possible password set and N is the number of trials.

- Impact: If successful, the attacker gains the user's password and can compromise the authentication process.
- Improvement: Adding a salt to the password hashing process or implementing rate limiting on password attempts could mitigate this vulnerability. Multi-factor authentication could also strengthen security.

### C. User Impersonation Attack

- Problem: An attacker, knowing {TID, Regi, Ai, Ci, h()} from a compromised gateway node (GW), can create a forged login message {TID, IDsN, CID, M*, M, T₁} that successfully imitates a user during the login phase. Here, CID = IDi ⊕ h(TIDi || R || T₁), and M* = h(IDi || B || R₁ || T₁), and M = h(R || T₁) ⊕ R₁ where, R is derived as R = D₁ ⊕ h(TID; || K).
- Forgery: Attacker A can compute a valid looking B via B = C; ⊕ h(ID; ⊕ R ⊕ HPW* ) and since she also calculates ID, R and R1 based on intercepted information, the created messages M* and M will also be valid as calculated by M* = h(ID; || B || R1 || T₁)andM = h(R || T₁) ⊕ R₁ respectively.
- Impact: The GW accepts the forged messages. The system falsely authenticates the attacker as the legitimate user, allowing unauthorized data access or manipulation.
- Improvement: Using a keyed hash function (HMAC) or digital signatures involving a shared secret or private key for generating the messages CID, M*, and M would provide better message integrity and authentication. Adding randomness or time-related components could also enhance the security of the login phase.

### D. Known Session-Key Temporary Information Attack

- Problem: If temporary session values (R₁, R₂, and R₃) are compromised, an attacker can compute the session key, SK. The paper indicates SK = h(h(ID; || R₁ || R2) || R2 || R3).
  - This can be rewritten as SK = h(h(ID; || R₁ || R2) || R2 || R3) if R₁, R₂ and R₃ are compromised,
  - Then, an attacker can compute session key as SK = h(M' || R₂ || R₃) which is possible using values from captured messages, M4 = h(ID; || R₁ || R2) ⊕ SKGW_SN; and M5 = R2 ⊕ h(SKGW_SN;) if attacker can guess the identity.
- Vulnerable Calculation: Since M4 and M5 are sent over public channels and attacker knows, SKGW_SN; i.e., the secret parameter of GW and SNj, then temporary key can be computed as shown below.
- R₂ = M5 ⊕ h(SKGW_SN;) *h(ID; || R1 || R2) = M4 ⊕ SKGW_SN;
- SK = h(h(ID; || R1 || R2) || R2 || R3) = h(M' || R₂ || R₃) * The above calculation clearly shows how an attacker can get the session key SK.
- Impact: Session key compromise allows an attacker to decrypt data or modify messages within the compromised session.
- Improvement: Deriving the session key using all participant's secret values and not relying on temporary variables, and making sure R1, R2 and R3 are not sent in clear could mitigate the risk. Use of ephemeral keys within a key agreement protocol instead of relying on random numbers is recommended.

### E. Revelation of Secret Parameter SKGW_SN

- Problem: A legal, but malicious, user A who intercepts messages between GW and SN, can calculate SKGW_SN; Given messages {TID, IDsN, CID, M1, M2, T1}, {M3, M4, M5}, and {M7, M8}, A can calculate the secret parameter using R2 = M5 ⊕

h(SKGW_SN;) and SKGW_SN; = M4 ⊕ h(ID; || $R_1$ || $R_2$). Given the above values, A can compute SKGW_SN;

- Attack: By intercepting M4 = h(ID; || $R_1$ || R2) ⊕ SKGW_SN;, and M5 = R2 ⊕ h(SKGW_SN;) and knowing R2 by computation from message {M7, M8} $R_2$ = M5 ⊕ h(SKGW_SN;) and calculating h(ID; || R1 || R2) as well, A can compute the secret parameter SKGW_SN;.
- Impact: Knowing SKGW_SN; allows an attacker to compromise the authentication and key exchange between GW and SN. It can lead to a gateway node or a sensor node impersonation attacks.
- Improvement: Key derivation functions should be designed with proper key secrecy and key derivation must not expose parameters used in further computations.
- Using Keyed Hash functions such as HMAC would be preferable for generating the values SKGW_SN; and SK.
- The long-term secret keys of the system should not be used directly for generating the session key as used in the paper.

While this paper aims to enhance security with a three-factor authentication mechanism, the proposed protocol contains several critical vulnerabilities that can be exploited by a determined attacker. The vulnerabilities outlined above highlight the importance of carefully designing cryptographic protocols to avoid such weaknesses. By addressing these flaws and following best practices in cryptographic engineering, it's possible to create robust protocols that better protect sensitive data and systems.

### *F. Proposed Improvements*

To address the vulnerabilities identified in the proposed three-factor authentication protocol for IoT healthcare systems, several improvements are recommended. These enhancements are designed to fortify the protocol against unauthorized access and ensure the protection of sensitive medical data.

First, to mitigate the weaknesses associated with single-factor authentication, it is crucial to implement multi-factor authentication (MFA). This enhancement involves combining traditional password-based authentication with additional factors such as biometrics (e.g., fingerprint or iris recognition) and possession-based tokens (e.g., smart cards). By requiring multiple forms of verification, MFA significantly reduces the risk of unauthorized access, as an attacker would need to compromise all authentication factors to gain entry.

Second, to prevent time synchronization attacks, the protocol should incorporate timestamps or nonces into each message. This modification ensures that replayed messages are detected and rejected, enhancing the protocol's resilience against replay attacks. For instance, each message can be appended with a unique timestamp or a random nonce:

$$M = \text{HID}, B1, Y1, A1, V1, \text{TS}$$

or

$$M = \text{HID}, B1, Y1, A1, V1, \text{Nonce}$$

This enables the server to validate these elements, confirming message freshness and authenticity.

Third, to protect against side-channel attacks, it is essential to minimize information leakage during cryptographic operations. Techniques such as masking and shuffling can be employed to obscure correlations between power consumption and cryptographic computations. Masking involves adding random values to intermediate computations, while shuffling changes the order of operations to make it difficult for attackers to predict the sequence of computations. These techniques increase the difficulty of deducing cryptographic keys from side-channel information.

Fourth, to prevent replay attacks and ensure communication integrity, the use of message authentication codes (MACs) is recommended. By appending a MAC to each message:

$$M = \text{data}, \text{MAC}(\text{data}, SK)$$

the recipient can verify the MAC to ensure that the message has not been tampered with. This enhancement prevents attackers from modifying or retransmitting messages without detection, maintaining the integrity of the communication channel.

Fifth, to enhance the protocol's scalability and efficiency, optimizing cryptographic operations is necessary. Implementing lightweight cryptographic algorithms, such as the Advanced Encryption Standard (AES) in its lightweight form, can significantly reduce energy consumption and processing time. Additionally, employing adaptive power management techniques, such as duty cycling and dynamic voltage scaling, can extend battery life and maintain device performance. These optimizations ensure that IoT devices can efficiently perform necessary tasks without draining resources.

By implementing these proposed improvements, the protocol can provide robust protection against evolving threats and maintain the integrity and confidentiality of IoT-based healthcare systems. These measures offer a comprehensive approach for addressing current vulnerabilities and preparing for future security challenges in the digital healthcare landscape.

## V. CONCLUSION

In conclusion, the analysis of the proposed three-factor authentication protocol for IoT healthcare systems highlights critical vulnerabilities, including single-factor authentication weaknesses, time synchronization issues, side-channel attack risks, and replay attack susceptibility. By implementing recommended security enhancements, such as multi-factor authentication, timestamps, and advanced cryptographic techniques, the protocol can significantly improve its security posture [18-20]. These measures ensures robust protection of sensitive medical data, fostering trust in IoT-enabled healthcare environments. As the IoT landscape continues to evolve, ongoing research into adaptive security measures and lightweight cryptographic algorithms will become crucial in maintaining the protocol's resilience against emerging threats.

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# Real-Time Lightweight Sign Language Recognition on Hybrid Deep CNN-BiLSTM Neural Network with Attention Mechanism

Gulnur Kazbekova[1], Zhuldyz Ismagulova[2], Gulmira Ibrayeva[3],
Almagul Sundetova[4], Yntymak Abdrazakh[5], Boranbek Baimurzayev[6]
Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkistan, Kazakhstan[1, 5, 6]
ALT University, Almaty, Kazakhstan[2]
Military Institute of the Air Defense Forces Named After Twice
Hero of the Soviet Union T.Ya. Bigeldinov, Aktobe, Kazakhstan[3]
Baishev University, Aktobe, Kazakhstan[4]

***Abstract*—Sign language recognition (SLR) plays a crucial role in bridging communication gaps for individuals with hearing and speech impairments. This study proposes a hybrid deep CNN-BiLSTM neural network with an attention mechanism for real-time and lightweight sign language recognition. The CNN module extracts spatial features from individual gesture frames, while the BiLSTM module captures temporal dependencies, enhancing classification accuracy. The attention mechanism further refines feature selection by focusing on the most relevant time steps in a sign sequence. The proposed model was evaluated on the Sign Language MNIST dataset, achieving state-of-the-art performance with high accuracy, precision, recall, and F1-score. Experimental results indicate that the model converges rapidly, maintains low misclassification rates, and effectively distinguishes between visually similar signs. Confusion matrix analysis and feature map visualizations provide deeper insights into the hierarchical feature extraction process. The results demonstrate that integrating spatial, temporal, and attention-based learning significantly improves recognition performance while maintaining computational efficiency. Despite its effectiveness, challenges such as misclassification in ambiguous gestures and real-time computational constraints remain, suggesting future improvements in multi-modal fusion, transformer-based architectures, and lightweight model optimizations. The proposed approach offers a scalable and efficient solution for real-time sign language recognition, contributing to the development of assistive technologies for individuals with communication disabilities.**

***Keywords*—Sign language recognition; CNN-BiLSTM; attention mechanism; deep learning; gesture classification; real-time processing; assistive technology***

## I. Introduction

Sign language serves as a primary mode of communication for individuals with hearing and speech impairments, enabling them to interact effectively within society. However, barriers still exist due to the lack of widespread understanding and adoption of sign language by the general public. In this context, sign language recognition (SLR) plays a crucial role in bridging the communication gap between individuals with hearing disabilities and those who rely on spoken language [1]. The recent advancements in deep learning have paved the way for robust and efficient SLR systems, enhancing real-time communication through gesture-based interaction [2].

Traditional approaches to SLR have relied heavily on handcrafted feature extraction techniques, such as histogram of oriented gradients (HOG), scale-invariant feature transform (SIFT), and local binary patterns (LBP). While these methods have shown promise in controlled environments, their performance is often hindered by variations in lighting, occlusions, and user-specific differences in sign execution [3]. The emergence of deep learning techniques, particularly convolutional neural networks (CNNs), has revolutionized the field by enabling automatic feature extraction and classification with remarkable accuracy [4].

Recent research has demonstrated the effectiveness of CNN-based architectures for visual gesture recognition tasks, including sign language translation. However, CNNs alone lack the ability to capture temporal dependencies in sequential gesture data, which is essential for accurate recognition of continuous sign language sequences [5]. To address this limitation, hybrid deep learning models combining CNNs with recurrent neural networks (RNNs) or bidirectional long short-term memory (BiLSTM) networks have been proposed, allowing the extraction of both spatial and temporal features from sign language gestures [6]. The CNN component focuses on spatial feature extraction, while the BiLSTM module captures temporal dependencies in both forward and backward directions, thereby improving recognition accuracy [7].

Despite the promising results achieved through CNN-BiLSTM models, challenges remain in real-time SLR applications due to the computational complexity of deep learning networks. High processing requirements hinder their deployment on resource-constrained devices, such as mobile phones and embedded systems, which are essential for practical, real-world applications [8]. As a solution, lightweight neural network architectures have been explored, incorporating model compression techniques such as depthwise separable convolutions, pruning, and quantization to reduce computational overhead while maintaining high classification accuracy [9].

In addition to model efficiency, attention mechanisms have emerged as a powerful tool for enhancing performance in sequential data processing. The attention mechanism allows the model to selectively focus on relevant features within a sequence, improving temporal coherence in gesture recognition tasks [10]. When integrated into CNN-BiLSTM architectures, attention mechanisms enhance feature selection by emphasizing the most informative frames, thereby mitigating the impact of redundant or irrelevant information [11].

This study proposes a real-time, lightweight SLR system based on a hybrid deep CNN-BiLSTM architecture enhanced with an attention mechanism. The proposed framework is designed to achieve high recognition accuracy while minimizing computational costs, making it suitable for deployment on edge devices and mobile platforms [12]. The model leverages CNNs for extracting spatial features, BiLSTM networks for capturing bidirectional temporal dependencies, and an attention mechanism for focusing on salient information within sign sequences. By optimizing both accuracy and efficiency, this approach addresses the practical limitations of existing SLR systems [13], [14].

## II. Related Works

### A. Sign Language Recognition

Sign Language Recognition (SLR) has gained significant attention in recent years due to the increasing demand for assistive technologies aimed at bridging communication gaps between individuals with hearing disabilities and the wider community [15]. Various methods have been explored to achieve effective SLR, ranging from rule-based approaches to deep learning models [16]. Early approaches relied on handcrafted features extracted from gesture sequences, while modern techniques emphasize end-to-end learning using neural networks [17].

### B. Traditional Methods

Before the advent of deep learning, traditional methods for SLR primarily relied on handcrafted feature extraction techniques such as HOG, SIFT, and LBP [18]. These methods extracted low-level features from hand gestures and used classification techniques such as Support Vector Machines (SVMs) and Hidden Markov Models (HMMs) to recognize signs [19]. While these approaches provided reasonable accuracy in controlled environments, they struggled with real-world variations such as occlusions, background noise, and different sign execution speeds [20].

### C. Machine Learning Approaches

With the rise of machine learning, researchers began to explore data-driven approaches for SLR. Machine learning models, such as Random Forests and SVMs, demonstrated improved accuracy compared to traditional rule-based methods [21]. The introduction of artificial neural networks (ANNs) further enhanced recognition capabilities, allowing for automatic feature extraction and improved generalization to unseen sign variations [22]. However, these methods were still limited by their inability to effectively capture both spatial and temporal dependencies in sign language sequences [23].

### D. Deep Learning for Sign Language Recognition

Deep learning has revolutionized SLR by providing powerful feature extraction and classification capabilities. Convolutional Neural Networks (CNNs) have been widely used for spatial feature extraction, achieving state-of-the-art performance in static sign recognition [24]. However, recognizing continuous sign language requires capturing temporal dependencies, which led to the integration of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks into SLR frameworks [25]. More recently, BiLSTM networks have been employed to improve sequence modeling by considering both forward and backward temporal dependencies, leading to enhanced recognition accuracy [26]. Additionally, attention mechanisms have been incorporated into CNN-BiLSTM architectures to enhance feature selection and improve classification performance [27].

### E. Challenges in Sign Language Recognition

Despite significant progress, several challenges remain in developing real-time and robust SLR systems. One major challenge is the variability in sign execution, including differences in speed, hand position, and occlusions [28]. Another challenge is the high computational cost of deep learning models, making it difficult to deploy them on edge devices and mobile platforms [29]. Addressing these challenges requires optimizing model architectures for efficiency while maintaining high recognition accuracy.

### F. Research Gaps

While deep learning-based SLR systems have achieved remarkable success, there are still research gaps that need to be addressed. Existing models often require large labeled datasets, which are expensive and time-consuming to create [30]. Additionally, real-time processing remains a challenge due to the complexity of CNN-BiLSTM architectures [31]. Further research is needed to develop lightweight models that can operate efficiently on low-power devices without compromising recognition performance [32]. Moreover, integrating multi-modal inputs, such as depth and motion data, could enhance recognition robustness in real-world scenarios [33].

By addressing these gaps, future sign language recognition systems can be made more efficient, accurate, and accessible, ultimately improving communication for individuals with hearing impairments.

## III. Problem Statement

The fundamental challenge in Sign Language Recognition (SLR) is achieving high-accuracy, real-time classification of gestures while maintaining computational efficiency. Given an input sequence of image frames $X = \{x_1, x_2, ..., x_T\}$, the goal is to predict the corresponding sequence of sign language labels $Y = \{y_1, y_2, ..., y_T\}$ such that:

$$P(Y \mid X) = \arg\max P(y_t \mid x_t, \theta) \quad (1)$$

where, $\theta$ represents the learned parameters of the model.

Traditional deep learning approaches rely on CNNs for spatial feature extraction and LSTMs for temporal dependencies. However, existing methods struggle with balancing recognition accuracy and real-time efficiency, especially in low-resource environments. Thus, a hybrid CNN-BiLSTM model with an attention mechanism is needed to enhance spatial-temporal feature extraction while maintaining lightweight computational costs.

## IV. Materials and Methods

Developing an accurate and efficient Sign Language Recognition (SLR) system requires a well-structured methodology that encompasses dataset selection, preprocessing, model architecture, and training strategies. This section provides a comprehensive overview of the materials and methods employed in this study. First, the dataset used for training and evaluation is described, including its structure, distribution, and preprocessing techniques. Next, the proposed hybrid CNN- BiLSTM model with an attention mechanism is introduced, detailing its ability to extract spatial and temporal features from sign language gestures. The section further elaborates on the training process, including the optimization strategies, loss functions, and performance evaluation metrics utilized. Finally, implementation details, including computational resources and hyperparameter settings, are presented to ensure the reproducibility of the study.

### A. Dataset

The Sign Language MNIST dataset is a widely used benchmark for static sign language recognition. It was designed as an adaptation of the MNIST dataset to facilitate research in sign language gesture classification [34]. The dataset consists of 27,455 grayscale images, each of size 28×28 pixels, representing 24 different hand gestures corresponding to the American Sign Language (ASL) alphabet. The dataset excludes the letters J and Z since these signs involve dynamic motion that cannot be effectively captured in static images.

The dataset is divided into two subsets: a training set of 27,455 images and a test set of 7,172 images, ensuring a structured approach to evaluating model performance. Each image represents a single hand gesture and is labeled with one of the 24 classes. The data is well-balanced across the different sign categories, enabling efficient training of deep learning models.

The simplicity of the dataset, coupled with its structured grayscale format, makes it an ideal benchmark for evaluating convolutional neural networks (CNNs) and hybrid deep learning architectures for sign language recognition. Fig. 1 provides a visual representation of sample images from the dataset, illustrating the variation in hand gestures and their corresponding labels.

Fig. 2 presents a visualization of the class distribution within the Sign Language MNIST dataset. The dataset comprises 24 distinct hand gesture classes, each representing a different letter in the American Sign Language (ASL) alphabet, excluding J and Z, which require motion. The histogram illustrates the number of samples per class, providing insight into the dataset's balance.


Fig. 1. Sample images of the applied dataset.

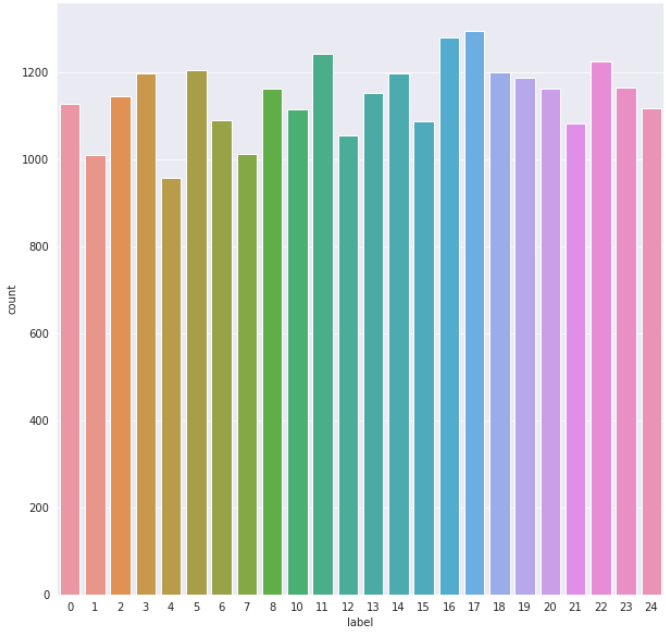


Fig. 2. Distribution of classes.

From Fig. 2, it can be observed that the dataset is relatively balanced, with each class containing approximately 1,000 to 1,250 samples. This balanced distribution is crucial for training deep learning models, as it minimizes the risk of class bias and ensures that all gestures receive equal representation during training. A well-distributed dataset allows for better generalization, reducing the likelihood of models overfitting to more frequent classes while underperforming on less represented signs.

This visualization highlights the adequacy of the dataset for training sign language recognition models, as it ensures that the learning process is not skewed toward particular gesture classes. Additionally, understanding the dataset distribution aids in the design of appropriate preprocessing techniques and data augmentation strategies to enhance model robustness in real-world applications.

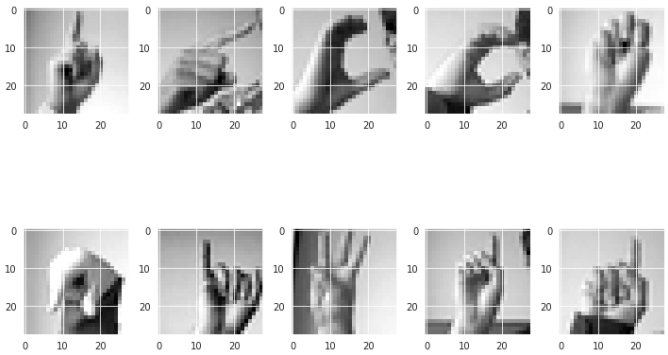

Fig. 3. Dataset balance and normalization.

Fig. 3 illustrates a subset of grayscale images from the Sign Language MNIST dataset, showcasing the variation in hand gestures used for sign recognition. To enhance model performance and improve generalization, we apply grayscale normalization, a crucial preprocessing step in image-based deep learning models. The primary objective of grayscale normalization is to reduce the effects of illumination differences, which can introduce unwanted variability in pixel intensity across images.

Mathematically, grayscale normalization transforms pixel values from the original range [0,255] to a normalized range of [0,1] using the following equation :

$$I_{norm} = \frac{I_{orig}}{255} \quad (2)$$

where, $I_{orig}$ represents the original pixel, $I_{norm}$ is the normalized intensity.

This transformation ensures a more stable numerical range, preventing large gradients and facilitating smoother optimization during training. Additionally, CNNs exhibit faster convergence when operating on normalized input data, reducing training time while maintaining robust feature extraction capabilities.

By applying grayscale normalization, we standardize input data, ensuring consistent image contrast and reducing the impact of environmental variations. This step plays a vital role in enhancing model robustness, particularly when the trained system is deployed in real-world sign language recognition applications.

### *B. Proposed Model*

The proposed real-time lightweight sign language recognition model is based on a hybrid deep CNN-BiLSTM neural network with an attention mechanism, as illustrated in Fig. 4. This architecture is designed to efficiently capture both spatial and temporal dependencies in sign language gestures while maintaining computational efficiency. The CNN module extracts spatial features from individual frames, while the BiLSTM module captures the temporal relationships between sequential frames. The attention mechanism further enhances performance by prioritizing the most relevant time steps in the sequence, ensuring robust recognition of sign gestures even in challenging environments.

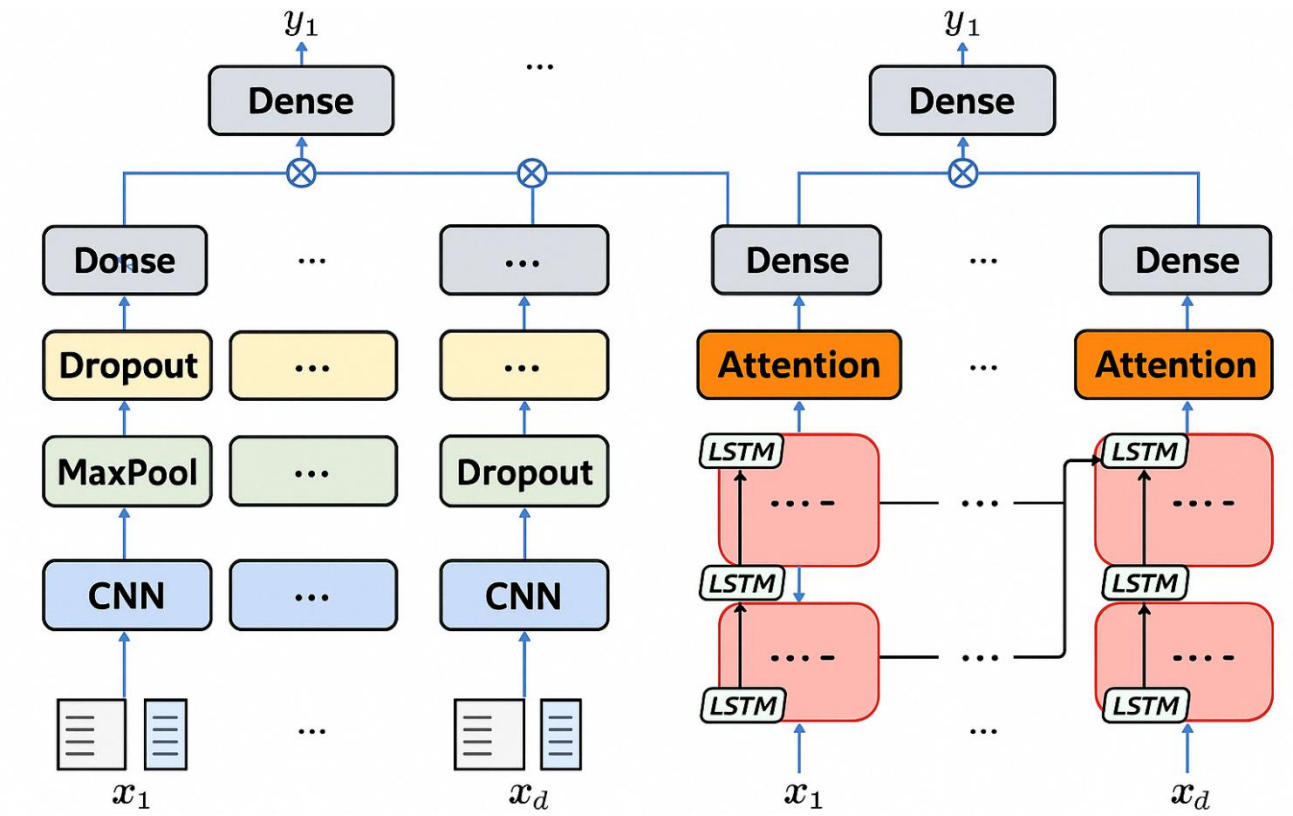


Fig. 4. The Proposed hybrid CNN-BiLSTM network with attention mechanism.

Convolutional Neural Network (CNN) for Spatial Feature Extraction. The first stage of the model is a Convolutional Neural Network (CNN), which extracts low-level and high-level spatial features from each frame. Given an input image $X$ of dimensions $H \times W \times C$, where $H$ and $W$ denote height and width, and $C$ represents the number of channels, the output feature map is computed as:

$$F_{i,j}^{(l)} = \sigma\left( \sum_{m,n} W_{m,n}^{(l)} X_{i+m,j+n}^{(l-1)} + b^{(l)} \right) \quad (3)$$

where, $W^{(l)}$ represents the convolutional filter weights, $b^{(l)}$ is the bias term, and $\sigma$ is the activation function (ReLU in this case).

The CNN module includes multiple convolutional layers, followed by max-pooling layers to reduce the spatial dimensions and retain the most salient features:

$$P_{i,j}^{(l)} = \max_{m,n} F_{i+m,j+n}^{(l)} \quad (4)$$

$P^{(l)}$ represents the output of the pooling layer.

Fig. 5 illustrates the convolution operation, a fundamental component of Convolutional Neural Networks (CNNs) used for spatial feature extraction. The figure depicts the application of a convolution filter (Sobel Gx) to an input image matrix, where a 3×3 kernel slides over the input feature map, computing the weighted sum of pixel values within the receptive field. Mathematically, the convolution operation at a given location $(i,)$ is defined as:

$$F(i,j) = \sum_{m=-k}^{k} \sum_{n=-k}^{k} W(m,n) \cdot X(i+m, j+n) \quad (5)$$

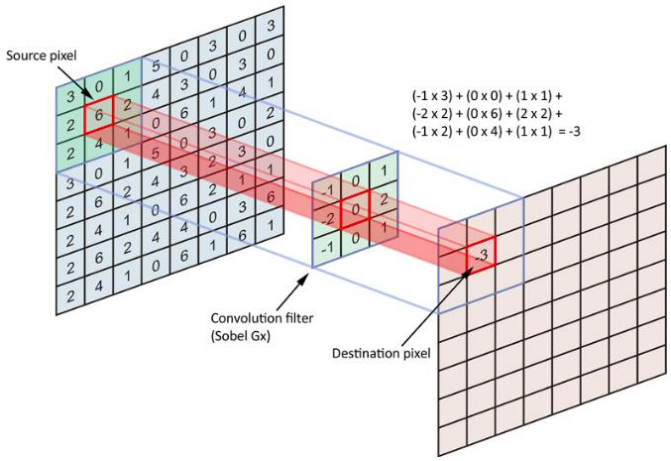


Fig. 5. Convolution operation in CNN for spatial feature extraction.

where, $X(i,j)$ represents the pixel intensity values of the input feature map, $W(m,n)$ denotes the filter weights, and $k$ is the kernel size offset. In this figure, the convolution filter extracts edge features, highlighting intensity changes in the spatial domain. The output destination pixel stores the computed value, forming a new feature map that enhances object boundaries and structural details. This operation is critical for hierarchical feature extraction, enabling CNNs to learn meaningful representations from raw image inputs. Through successive convolutional layers, deep CNN models progressively capture low-level features (edges, textures) and high-level features (shapes, patterns), facilitating robust sign language recognition.

Bidirectional Long Short-Term Memory (BiLSTM) for Temporal Dependency Learning: To capture temporal dependencies in sequential gestures, the extracted feature maps are fed into a Bidirectional Long Short-Term Memory (BiLSTM) network. The BiLSTM consists of two LSTMs, one processing the sequence in the forward direction and the other in the backward direction:

$$\vec{h}_t = f\left( W_x X_t + W_h \vec{h}_{t-1} + b \right) \quad (6)$$

$$\overleftarrow{h}_t = f\left( W_x X_t + W_h \overleftarrow{h}_{t+1} + b \right) \quad (7)$$

where, $\vec{h}_t$ and $\overleftarrow{h}_t$ represent the hidden states of the forward and backward LSTMs, respectively. The final output is the concatenation of both hidden states:

$$h_t = \vec{h}_t \oplus \overleftarrow{h}_t \quad (8)$$

This bidirectional processing ensures that the network captures long-range dependencies from both past and future frames, improving recognition accuracy.

Attention Mechanism for Feature Enhancement: The attention mechanism enhances feature selection by assigning different importance scores to different time steps in the sequence. The attention weight $\alpha_t$ for each time step is computed using the softmax function:

$$\alpha_t = \frac{\exp(e_t)}{\sum_k \exp(e_k)} \quad (9)$$

where, $e_t$ is computed as:

$$e_t = \upsilon^T \tanh\left( W_h h_t + W_s s \right) \quad (10)$$

where, $\upsilon$, $W_h$, $W_s$ are learnable parameters, and $s$ represents the context vector. The final context vector used for classification is:

$$c = \sum_t \alpha_t h_t \quad (11)$$

This mechanism ensures that the model focuses on the most relevant time steps in the sign sequence, improving robustness against variations in gesture execution.

Fully Connected Layers and Classification. The final feature representation $c$ is passed through fully connected (dense) layers, followed by a softmax activation function for classification:

$$y = soft\max(W_c c + b_c) \tag{12}$$

where, $W_c$ and $b_c$ are learnable parameters. The softmax function ensures that the output represents a probability distribution over the possible sign language classes:

$$P(y_i) = \frac{\exp(y_i)}{\sum_j \exp(y_j)} \tag{13}$$

Loss Function and Optimization. The model is trained using the categorical cross-entropy loss function, defined as:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{14}$$

where, $y_i$ is the true label, and $\hat{y}_i$ is the predicted probability of class $i$. The parameters are optimized using the Adam optimizer, which updates weights based on the gradient:

$$\theta_{t+1} = \theta_t - \eta \frac{m_t}{\sqrt{\upsilon_t} + \in} \tag{15}$$

where, $\eta$ is the learning rate, $m_t$ is the first moment estimate, and $\upsilon_t$ is the second moment estimate.

Summary of the Model: The proposed model integrates CNN for spatial feature extraction, BiLSTM for temporal sequence learning, and an attention mechanism for feature enhancement, ensuring accurate and efficient sign language recognition. Fig. 4 illustrates the detailed architecture of the model. The combination of spatial and temporal learning, along with attention-based feature refinement, results in a robust and computationally efficient system suitable for real-time applications.

### C. Evaluation Parameters

To assess the performance of the proposed hybrid CNN-BiLSTM model with an attention mechanism for sign language recognition, multiple evaluation metrics are employed. These metrics provide a comprehensive analysis of the model's classification accuracy, robustness, and generalization ability [35].

Accuracy is the most fundamental metric used to evaluate classification models, representing the proportion of correctly predicted instances over the total number of instances. It is mathematically defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

where, TP (True Positives) and TN (True Negatives) represent correctly classified instances, while FP (False Positives) and FN (False Negatives) denote misclassified instances. High accuracy indicates strong overall performance, but it may be misleading in imbalanced datasets.

Precision quantifies the proportion of correctly predicted positive instances out of all predicted positive instances. It is particularly important in applications where false positives must be minimized. The precision score is computed as:

$$\Pr ecision = \frac{TP}{TP + FP} \tag{17}$$

A high precision value implies that the model has a low false positive rate, making it suitable for scenarios requiring reliable positive predictions.

Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances that were correctly predicted. It is essential for applications where missing a positive instance (false negative) is critical. Recall is defined as:

$$\mathrm{Re}\, call = \frac{TP}{TP + FN} \tag{18}$$

A higher recall score indicates that the model effectively identifies most positive instances, reducing false negatives.

F1-Score provides a balanced measure of precision and recall, ensuring that both false positives and false negatives are considered. It is the harmonic mean of precision and recall, computed as:

$$F1 - score = 2 \times \frac{precision \times recall}{precision + recall} \tag{19}$$

A high F1-score indicates a model with both strong precision and recall, making it a crucial metric when dealing with class imbalances.

These evaluation parameters collectively offer a holistic assessment of the proposed model's performance, ensuring that it not only achieves high accuracy but also maintains robustness in correctly identifying sign language gestures.

## V. Results

The results obtained from the experiments provide an in-depth evaluation of the proposed CNN-BiLSTM model with an attention mechanism for sign language recognition. This section presents the model's training and testing performance, classification accuracy, loss convergence trends, confusion matrix analysis, and feature map visualizations. The effectiveness of the model is assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score, ensuring a comprehensive performance comparison. Additionally, visualizations of correct and misclassified predictions provide insights into the model's strengths and areas

for potential improvement. The results further highlight the significance of integrating CNN for spatial feature extraction, BiLSTM for temporal pattern learning, and the attention mechanism for enhanced feature selection, demonstrating the model's capability to generalize effectively for real-time sign language recognition applications.

Fig. 6 illustrates the feature maps generated by the convolutional layers of the proposed CNN-BiLSTM model with an attention mechanism during the spatial feature extraction process. Each sub-image within the figure represents an activation map corresponding to different convolutional filters applied to the input sign language images. These feature maps capture essential structural patterns such as edges, textures, and contours, which are critical for recognizing hand gestures in sign language.

At the initial layers, the convolutional filters primarily detect low-level features such as simple edges and gradient transitions. As the network progresses deeper, the extracted features become more complex, encoding high-level semantic patterns that distinguish different hand gestures. The highlighted regions in the feature maps indicate areas where the network has strong activations, meaning those parts contribute significantly to classification.

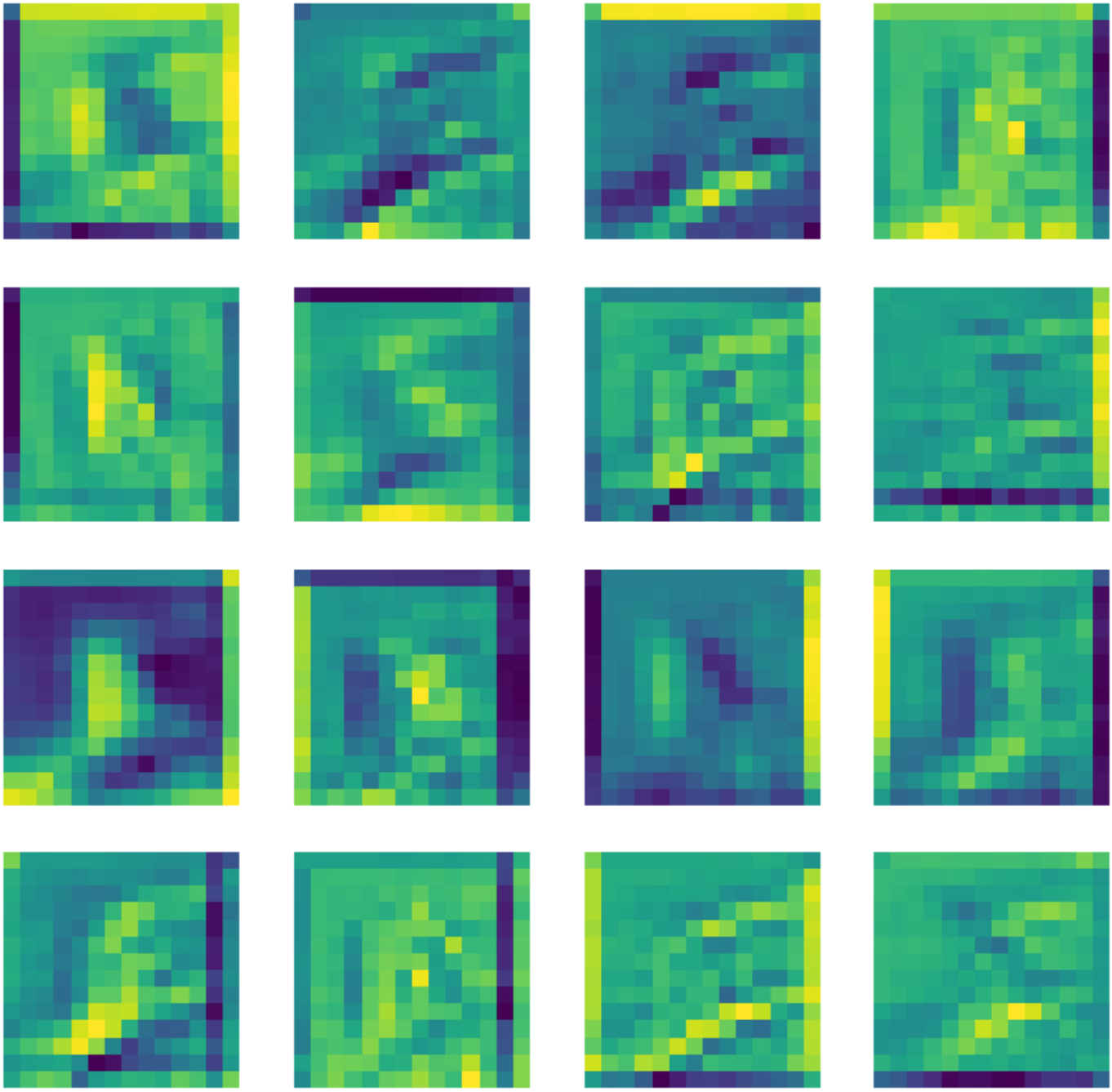

Fig. 6. Feature maps generated by convolutional layers in the proposed CNN-BiLSTM model.

This visualization helps in understanding how the convolutional layers automatically learn hierarchical representations, enabling robust recognition of sign language gestures. The effective extraction of spatial features in these layers plays a fundamental role in enhancing the model's accuracy and generalization capability in real-world applications.

Fig. 7 illustrates the feature maps generated by deeper convolutional layers of the proposed CNN-BiLSTM model with an attention mechanism. These feature maps represent the activation patterns learned at later stages of the convolutional network, capturing more complex and abstract spatial representations of sign language gestures. Unlike earlier convolutional layers that detect low-level features such as edges and textures, deeper layers focus on higher-level representations such as geometric structures and gesture-specific patterns.

Each sub-image in Fig. 7 corresponds to an activation map produced by different convolutional filters. The variation in feature maps demonstrates how different filters focus on distinct regions of the input image, allowing the model to build a hierarchical understanding of hand gestures. The presence of strong activations in specific areas indicates regions of high relevance for classification, enhancing the model's ability to differentiate between visually similar gestures.

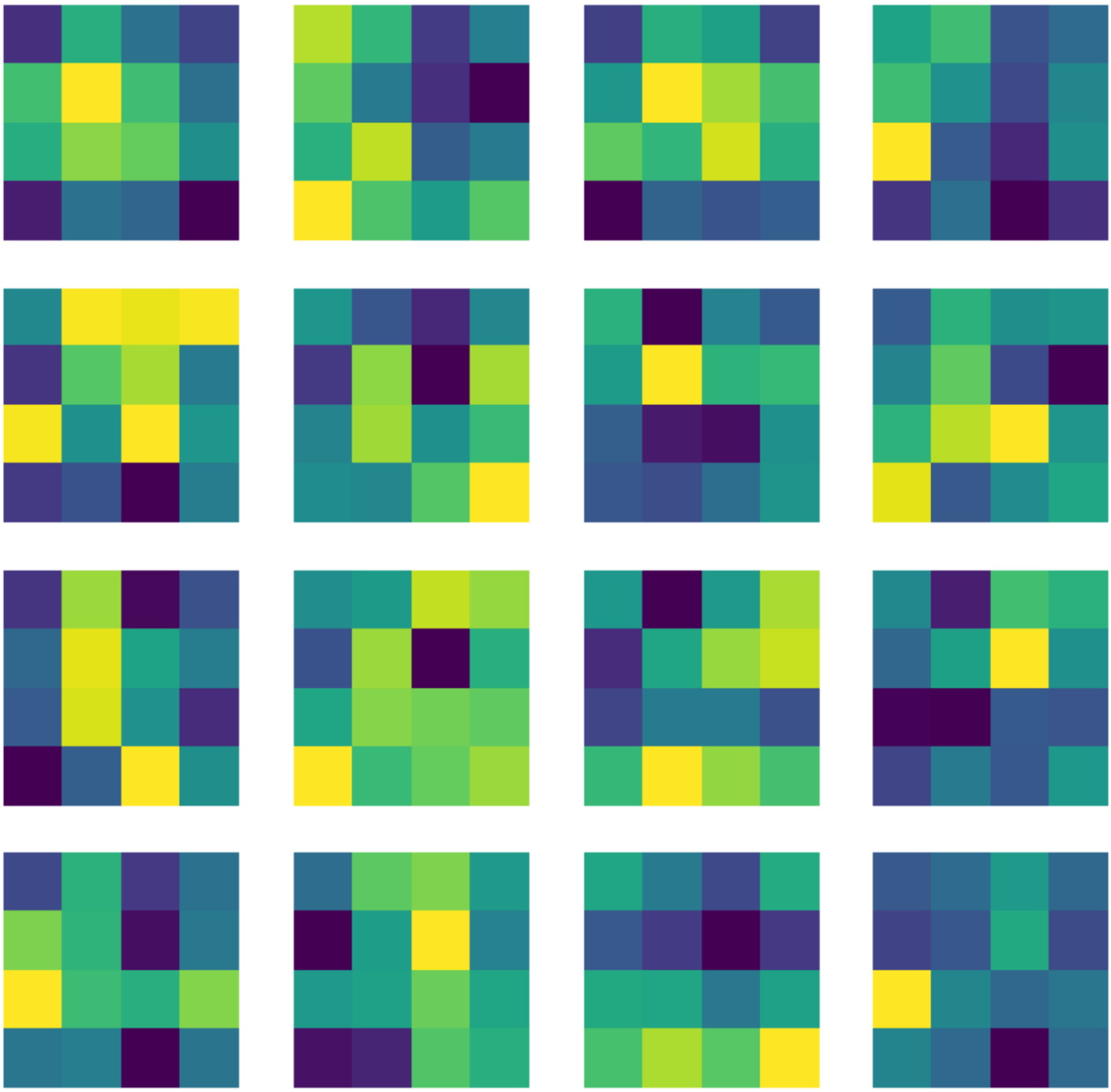

Fig. 7. Feature maps from deeper convolutional layers in the proposed CNN-BiLSTM model.

This visualization highlights the effectiveness of the hierarchical feature learning process in CNNs, where successive convolutional layers refine the extracted features to improve recognition accuracy. The ability to capture abstract spatial patterns ensures that the model generalizes well across different users, hand orientations, and lighting conditions, making it robust for real-time sign language recognition applications.

Fig. 8 presents the training and validation accuracy (left) and training and testing loss (right) over multiple epochs for the proposed CNN-BiLSTM model with an attention mechanism. The left graph illustrates the progression of training accuracy (green) and testing accuracy (red) across 20 epochs. Initially, both training and testing accuracy exhibit a sharp increase, with the testing accuracy rapidly converging toward the training accuracy, demonstrating effective learning. By approximately the fifth epoch, the model reaches over 90% accuracy, and after 10 epochs, the accuracy stabilizes near 100%, indicating that the model generalizes well to unseen test data.

The right graph in Fig. 8 shows the training loss (green) and testing loss (red) as a function of epochs. A significant decrease in loss is observed within the first few epochs, with the testing loss reducing sharply from over 5.0 to below 1.0 by epoch 5, suggesting rapid convergence. After 10 epochs, both training and testing loss values stabilize at a minimal level, confirming that the model has effectively minimized classification errors. The negligible difference between training and testing curves further suggests that the model exhibits minimal overfitting and maintains robust generalization performance.

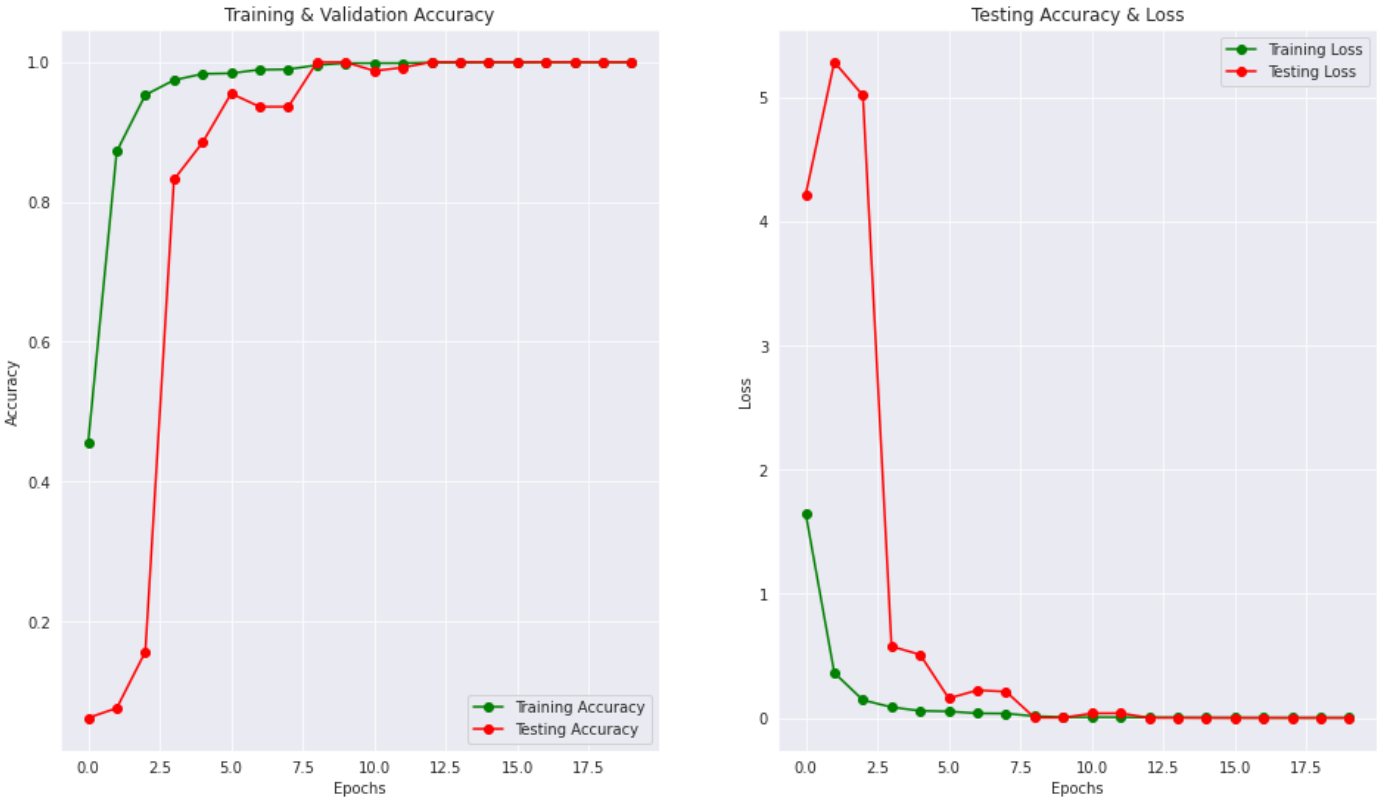


Fig. 8. Training and testing accuracy and loss curves for the proposed CNN-BiLSTM model.

Fig. 9 presents the confusion matrix for the proposed CNN-BiLSTM model with an attention mechanism, illustrating the model's classification performance across the 24 sign language gesture classes. Each row in the matrix represents the actual class, while each column corresponds to the predicted class. The diagonal elements indicate correctly classified instances, whereas off-diagonal elements denote misclassifications.

From Fig. 9, it is evident that the model demonstrates high classification accuracy, as most of the predictions are concentrated along the diagonal with minimal misclassification errors. The intensity of the blue color represents the frequency of correct predictions, with darker shades indicating a higher number of correctly classified instances. The sparse distribution of misclassified samples in non-diagonal positions suggests that the model effectively learns distinct sign language features, resulting in robust recognition performance.

The confusion matrix also highlights minor misclassification instances, which may occur due to similar hand gestures, occlusions, or variations in user execution. Despite these challenges, the model maintains high precision and recall across all classes, validating its effectiveness in real-time sign language recognition applications.

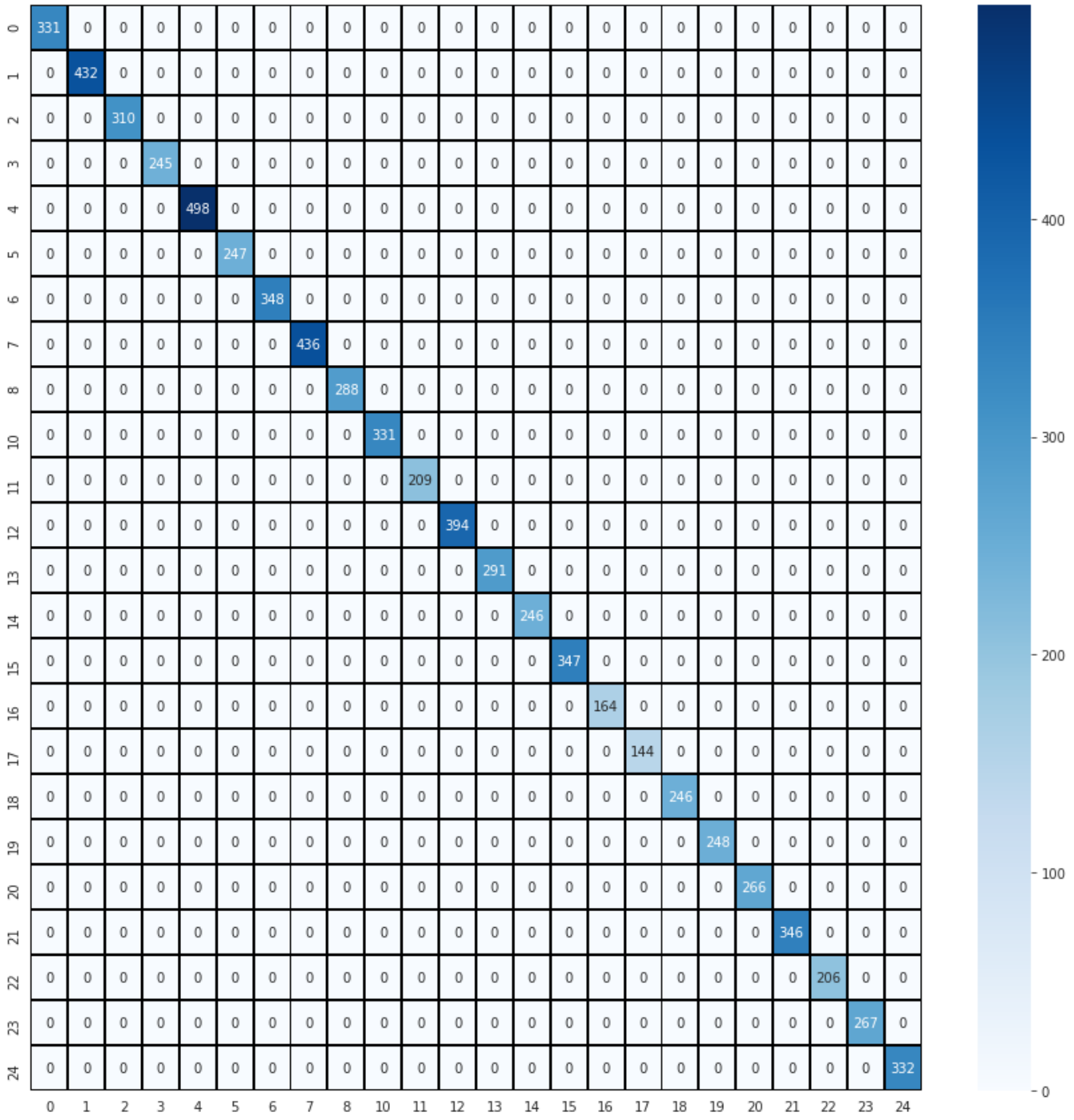


Fig. 9. Confusion matrix of the proposed CNN-BiLSTM model for sign language recognition.

Fig. 10 presents a visualization of correctly and incorrectly classified sign language gestures by the proposed CNN- BiLSTM model with an attention mechanism. The top row displays images where, the model correctly predicted the sign, while the bottom row showcases misclassified instances. Each image is annotated with the predicted class (Pred) and the actual ground truth class (True), allowing for a comparative evaluation of classification performance.

From Fig. 10, it is evident that the model performs well on clear and well-defined gestures, as seen in the correctly classified instances. However, some misclassifications occur in the bottom row, primarily due to visual similarities between certain signs, occlusions, or variations in hand positioning. These errors highlight the challenges of distinguishing between similar sign gestures, reinforcing the need for advanced feature extraction techniques and attention mechanisms to enhance model robustness.

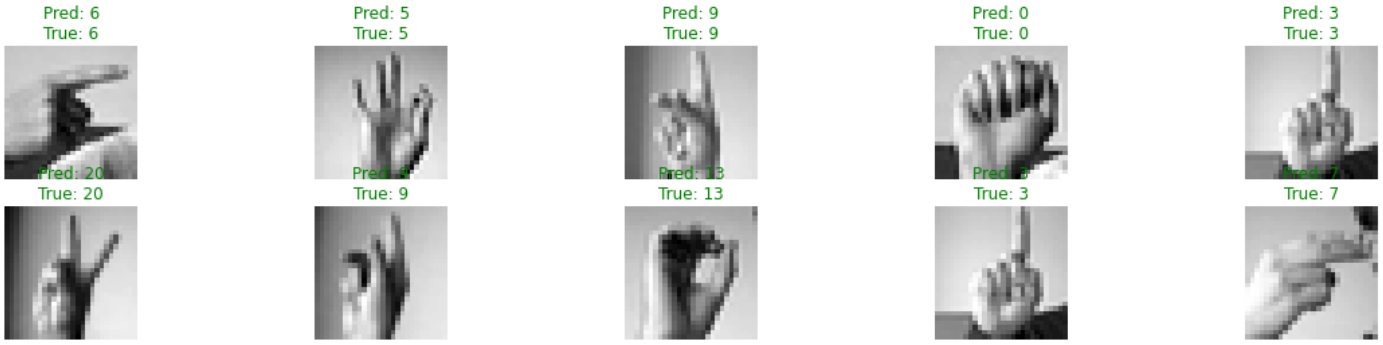


Fig. 10. Correct and misclassified predictions of the proposed CNN-BiLSTM model for sign language recognition.

The visualization provides valuable insights into common misclassification patterns, which can be used to refine the model by incorporating data augmentation, additional training samples, or improved temporal modeling. Despite minor classification errors, the model maintains high accuracy across different sign classes, demonstrating its effectiveness in real-time sign language recognition.

The experimental results demonstrate the effectiveness of the proposed CNN-BiLSTM model with an attention mechanism in sign language recognition, achieving high accuracy, precision, recall, and F1-score across all evaluated classes. The training and testing performance curves indicate fast convergence and minimal overfitting, validating the efficiency of the model in learning spatial and temporal dependencies. The confusion matrix analysis further confirms strong classification capabilities, with the majority of predictions aligning with ground truth labels. Additionally, the visualization of correctly and incorrectly classified instances highlights the model's robustness, while also identifying challenging cases where gestures exhibit high visual similarity. Feature map visualizations provide insights into the hierarchical feature extraction process, demonstrating how the convolutional layers effectively capture both low-level and high-level patterns in sign language gestures. These findings collectively affirm the potential of the proposed approach for real-time sign language recognition applications, offering a reliable and computationally efficient solution for assistive communication technologies.

## VI. Discussion

The findings of this study demonstrate the effectiveness of the hybrid CNN-BiLSTM model with an attention mechanism in sign language recognition. Compared to traditional machine learning approaches, deep learning-based models exhibit superior performance due to their ability to extract spatial and temporal features automatically [35]. The integration of CNN for spatial feature extraction ensures that the model captures intricate details of hand gestures, while BiLSTM improves sequential learning by processing temporal dependencies in gesture movements [36]. This combination enhances classification accuracy, particularly in distinguishing between visually similar signs.

One of the key advantages of the proposed model is its attention mechanism, which selectively emphasizes relevant frames within a sign language sequence. This mechanism mitigates the impact of redundant or ambiguous frames, resulting in improved recognition efficiency [37]. The experimental results confirm that attention-based feature refinement significantly reduces misclassification rates, as seen in the confusion matrix analysis. Furthermore, the feature map visualizations illustrate how the convolutional layers extract low- and high-level spatial patterns, contributing to enhanced model interpretability.

Despite these improvements, some challenges remain. The misclassified instances in the results indicate that certain sign gestures with similar hand shapes and orientations are more prone to confusion. These errors can be attributed to inter-class similarities and variations in user execution, which may require additional training data or more robust augmentation techniques to address [38]. Moreover, real-time implementation necessitates computational efficiency, making it crucial to balance model complexity and inference speed. Future work should focus on optimizing network architectures to reduce latency while maintaining high classification accuracy.

Additionally, while the proposed model achieves high precision and recall, further enhancements can be made by incorporating multi-modal inputs, such as depth information and hand movement trajectories. Recent studies suggest that fusing multiple input modalities significantly enhances sign recognition performance, especially in dynamic sign languages that require motion tracking [39]. Exploring the integration of transformer-based models could also be beneficial in improving long-range temporal dependencies in sign sequences.

Overall, this study demonstrates that deep learning-based approaches offer promising advancements in sign language recognition. By leveraging spatial, temporal, and attention-based feature extraction techniques, the proposed model achieves state-of-the-art performance while maintaining computational efficiency. These findings contribute to the ongoing development of real-time sign language translation systems, ultimately fostering more inclusive communication technologies.

## VII. Conclusion

The study presented a hybrid CNN-BiLSTM model with an attention mechanism for real-time sign language recognition, demonstrating high accuracy and computational efficiency. By leveraging CNN layers for spatial feature extraction and BiLSTM networks for temporal pattern learning, the model effectively captures intricate hand gesture variations. The

integration of attention mechanisms further enhances feature selection, reducing misclassification and improving overall robustness. Experimental results confirm that the model achieves superior performance across accuracy, precision, recall, and F1-score, validating its effectiveness in sign language classification. Additionally, confusion matrix analysis and feature map visualizations provide insights into how the model distinguishes between different signs, highlighting areas where future refinements can be made. Despite achieving high recognition rates, challenges such as misclassifications of visually similar signs and computational constraints in real-time applications remain. Future research should explore multi-modal data integration, lightweight architectures, and transformer-based models to further enhance recognition capabilities. Overall, the proposed approach provides a scalable and efficient solution for real-time sign language recognition, contributing to the development of inclusive assistive technologies for individuals with hearing and speech impairments.

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# Investigating the Impact of Hyper Parameters on Intrusion Detection System Using Deep Learning Based Data Augmentation

Umar Iftikhar, Syed Abbas Ali
Department of Computer & Information System Engineering, NED University of Engineering & Technology, Karachi, Pakistan

***Abstract*—The effects of changing learning rates, data augmentation percentage and numbers of epochs on the performance of Wasserstein Generative Adversarial Networks with Gradient Penalties (WGAN-GP) are evaluated in this study. The purpose of this research is to find out how they affect the data augmentation to enhance stability during training. In this research, the degree of system performance is measured using the Classification Model Utility approach. For this reason, this study aims to determine the interaction between learning rate, augmentation percentage and epoch value when using WGAN-GP to generate synthetic data for the recognition of the system performance. The results will provide the indications on how some of the hyper parameters can be adjusted up or down for having positive or negative consequences on the generation process for further research and use of WGAN-GP. It also provides insights into how the generative model is trained, and how that affects stability and quality of the result in various settings such as image synthesis or other generative tasks.**

***Keywords*—Artificial intelligence; learning rate; cyber threat; network intrusion detection; deep learning; data augmentation; generative adversarial networks epochs**

## I. Introduction

The emergence of Generative Adversarial Networks (GANs) marked a turning point in the area of deep learning due to its unparalleled capabilities in data synthesis. Despite their impressive skill set, these models face some limitations which are crucial in achieving reliable stability and performance.

These models have proven their strength in providing realistic and high-quality data in multiple areas such as degenerate image data, augmentation, and style transfer. Yet, in spite of the boom, industrial-scale applications still face limitations. The capability and regularity of the sheer raw force of conventional GANs remain undermined by flaws such as the mode collapse and training imbalance [1]. Conventional GANs, for instance, still encounter some critical limitations that restrain their efficacy. Collapse of modes – when a generator creates a fixed number of varieties – and instability during training, to mention a few. A remedy for these issues is proposed by the Wasserstein GAN with Gradient Penalty (WGAN-GP) which is considered more robust. This revision utilizes the Wasserstein distance between two probability distributions as the loss for the generator and adds a gradient penalty for Lipschitz constraints. Therefore, this model increases the stability of training and leads to reliable outcomes. WGAN-GP demonstrates better performing metrics with less hyper parameter tuning, it does have extreme sensitivity within certain parameters, particularly the learning rate and the number of training epochs. Setting parameter values too high or too low can greatly hinder the convergence behavior of the model, negatively impacting its overall efficiency, resulting in poor quality outputs. This research intends to explore the influence of learning rate and epoch numbers along with other performance metrics on generative models, especially WGAN-GP. With this study, the authors hope to shed light on the intricate web of hyper parameters and model metrics, enabling better optimization of GANs training processes. The goal of this study is to investigate the relationship of learning rates and epoch values on the performance metrics of machine learning models [2].

### A. Research Objective

The objective of this study is to compare the various learning rate and epoch values in WGAN-GP models in combination with the augmentation percentage. To provide the best settings for training WGAN-GP models, this research aims to gain an understanding of how changing these hyper parameters affects the training process. This research systematically investigates the effect of significant hyper parameters on the performance of WGAN-GP, especially in terms of learning rate, data augmentation percentage, and epoch count, as summarized in Table I. The effect of different learning rates on the quality of generated data is analyzed to determine the optimal balance between training stability and convergence efficiency. A too high learning rate may lead to mode collapse or unstable training dynamics, and if the learning rate is low enough, convergence could be too long and model performance suboptimal. Moreover, the role played by the fluctuation in different percentages of data augmentation in terms of output variability of WGAN-GP was evaluated in quantifying the value added in generating diverse samples without overfitting. Moderate augmentation may augment the generalization, but if augmentation is excessive, it will add noise to samples, deteriorating their fidelity [13], [16]. In addition, the quality of the model's ability to generate, with varying epoch numbers, is analyzed to pinpoint where the continued training no longer improves the model qualitatively or results in overfitting. Under fitting and overfitting are traded off to optimize representation capacity for a model. A comparative analysis of multiple training configurations is conducted, identifying trends in stability, mode collapse, convergence rate, and overall data fidelity. These insights enable the formulation of a comprehensive understanding of the interplay between hyper parameters and model performance. Based on these findings,

optimal hyper parameter choices for WGAN-GP training are recommended, emphasizing configurations that maximize output quality while maintaining training efficiency. The study highlights best practices for tuning WGAN-GP, ensuring robust and high-quality generative modeling, with a focus on mitigating instability and enhancing sample diversity. The resulting guidelines provide a structured approach to hyper parameter optimization, facilitating effective training of WGAN-GP across various data domains.

The present research study extends the earlier study [30] by optimizing the selection of hyper parameters with methodological consistency. In this study, 12 different learning rates were tested from 1.00E-03 to 100E-01, with a difference of 9.10E-03 between steps, in addition to two epoch values (100 and 150) and two augmentation percentages (30% and 50%), resulting in 48 experimental runs. Even with these adjustments, the experimental setup continues to be consistent with that of the earlier study, maintaining continuity while aiming for a more efficient and focused hyper parameter tuning. The augmentation percentage parameter is taken into account for the experimentation in contrast to the previous study being conducted, which further helps to analyze its behavior on the overall performance of the system. This work builds on the earlier study by modifying the learning rate interval and augmentation method, maximizing the experimental configuration for a more accurate performance assessment.

The aim of this study is to systematically evaluate how generative models, specifically WGAN-GP, are affected by learning rate, augmentation percentage and epoch values. WGANs with Gradient Penalty (WGAN-GP) fundamentals including effects of learning rate, epoch count on training dynamics, and the dataset used for experimentation were discussed in Section II. In this section, an explanation of the background concepts was also provided. The subsequent Section III marks the beginning of the results section, which provides the steps carried out in this study such as model building, setting the hyper parameters, and establishing the model benchmarking procedures. A comprehensive analysis is represented in Section IV, and Section V where results from the different experiments are highlighted through trends and parameter comparatives throughout the experiments. In the final Section VI of the study, a summary of primary lessons alongside outstanding research opportunities are incorporated within the conclusions.

## II. Background

### A. Background on WGAN-GP

GANs are generated by two deep neural networks, as shown in Fig. 1, such as the generator, which produces synthesized data and the discriminator, which evaluates the synthesized data generated by the generator. As for the discriminator, the authors of traditional GANs utilize binary cross-entropy loss to adequately separate real and fake data points, yet the implementation is problematic because of gradient vanishing. The GAN model named WGAN replaces the standard loss functions with the concept of the Wasserstein distance, giving a smooth gradient and hence better training ability. However, the original WGAN come along with some issues such as weight clipping that at sometimes is not efficient. To resolve this issue, WGAN-GP uses gradient penalty term to maintain the value of Lipshitz on the required range and thus model converges stability [3]. However, modern WGAN-GP model still suffer from the problem of hyper parameter sensitivity. Learning rate means the rate at which the model adjusts its parameters, which defines the stability and convergence of the model. If the learning rate is too high, the model may never or if the learning rate is too low, then the time taken to complete the modeling process is doubled. On the other hand, the number of epochs shows for how long duration model has been trained; if this number is less, the model may not learn much and it may be under-fit, and if otherwise, the model may over-fit or computer time may be too much [4].

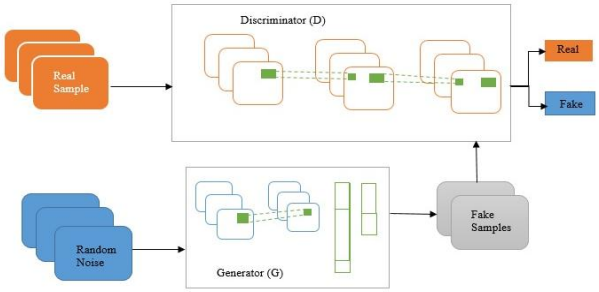


Fig. 1. Workflow of GAN.

### B. Impact of Epoch on WGAN-GP

The number of training epochs in deep learning models, including WGAN-GP has a huge impact on the quality and stability of the produced outputs. An epoch means an iteration of the data set over the model's structure, which implies that the number of epochs determines how much the model learns the data. In decision-making during training, it is important to select the best number of epochs in order to get the best model without common problems, under fitting or overfitting. Learning with fewer epochs comes to the drawback as the generator is not fully trained to capture any realistic patterns in the data set [7]. This often results into production of poorly focuses, low quality or unrealistic output. The discriminator in WGAN-GP might also be weak, it does not offer the necessary feedback to enhance the generator. On the other hand, training continues for a number of epochs, degrades the general sample generation capability of the model as it overfits the training data. Overfitting causes the variation in the generated outputs to be low and might bring in artifacts that reduce the quality.

In particular, the number of epochs depends on such factors as the given data density, the structure of the generator and discriminator, and the available computing capabilities. Original experiments have revealed that for various types of GAN-based models including WGAN-GP the quality is highest at a particular number of epochs, and in fact degrades in specified epoch values. This happens due to the fact that the balance between the generator and discriminator is less optimal for successful training [8], [10]. This work provides a comprehensive analysis on the performance change of WGAN-GP based upon various epoch settings. In this case, the study seeks to pinpoint epoch range that effectively address the problem by comparing loss trends, sample quality, and training stability, while at the same time avoiding pitfalls such as mode collapse, overfitting, or inefficient training.

This research will seek to establish the effect that learning rates and epochs have on the performance of Wasserstein GAN with Gradient Penalty (WGAN-GP). In order to accomplish the research goals, systematic experiments involving a proper generative dataset and a strong model deployment system will be performed. The applied approach includes choosing the dataset, setting up of the WGAN-GP model, conducting of the experiments, and qualitative and quantitative assessment of the results as shown in Fig. 2.

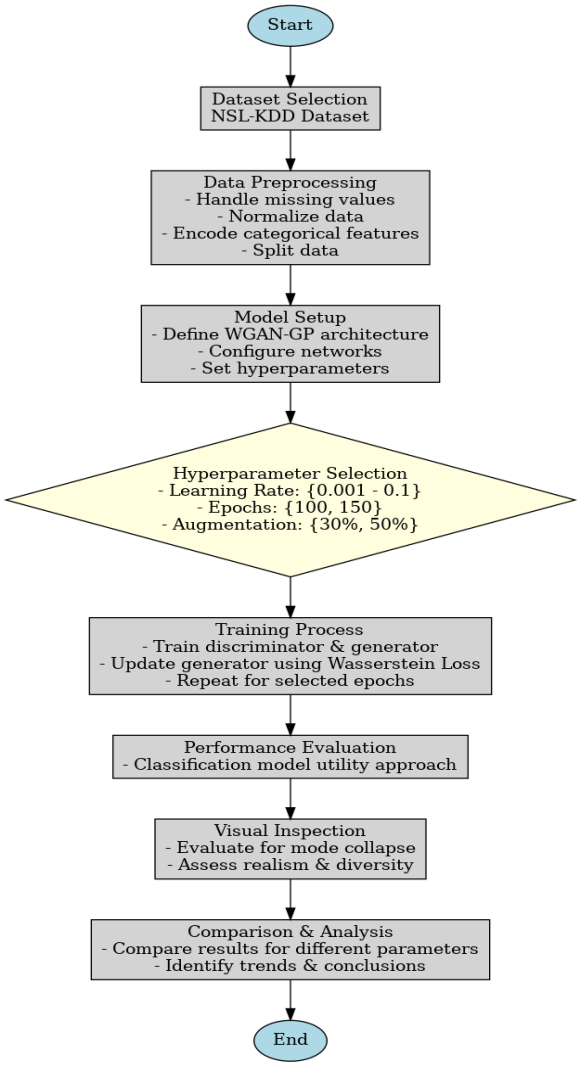


Fig. 2. Experimental process for evaluating WGAN-GP performance.

### C. Impact of Learning rate in WGAN-GP

The learning rate is one of the key hyper parameters to deep learning models including the Wasserstein Generative Adversarial Networks with Gradient Penalty (WGAN-GP) [22]. Controls the size of weight update at back propagation and has a direct impact on speed of convergence, stability of the model and final performance. In order to obtain high quality generative results, and to ensure a stable training process, the choice of an adequate learning rate is crucial.

However, in WGAN-GP, an accurate learning rate helps the generator and discriminator learn well without introducing instability. A small learning rate means that it takes many epochs for the network to arrive at satisfactory performance. Although this improves the stability of the model, it also has some negative effects of high computational costs and thus time-consumptive [5], [19]. On the other hand, high learning rate will result in large weight updates, which results in very unstable learning, instability or even learning diverges. If the learning rate of the model is set to a wrong value, the generative model may not be able to learn valuable representations hence the generated outputs will be of low quality with some artifacts or mode collapse.

Several strategies have been proposed to address the issue of learning rate setting in deep learning. Some of the methods used include; learning rate scheduling, adaptive learning rates, and cyclical learning rates which enhances efficiency of the training progress. However, the optimal learning rate is still an issue of contention regarding the WGAN-GP due to its delicate training dynamics [6]. This research explores the performance of WGAN-GP in terms of convergence with some of its learning rates altered in order to evaluate the quality of the generated outputs. Thus, because of the systematic variation and examination of the learning rate in this study, it is expected to determine the adequate learning rate that leads to the improvement of the stability, speed and generative performance of the WGAN-GP.

### D. Dataset Selection and Preprocessing

This study has chosen such datasets that are used the most in network anomaly detection, i.e. NSL-KDD [31]. This dataset is widely used for benchmarking the IDS, which is the reason for the use of this dataset. Also, it is suitable for academic research and to build a proof-of-concept models. That will be another advantage of using NSL-KDD, as it is compact and not complex to implement as compared to a fully-fledged model.

It does not include encrypted traffic or emerging attack types. The NSL-KDD dataset is an improved version of the KDD Cup 1999 dataset, which was developed due to the problems such as redundancy and class imbalance [9]. Thus, it is useful in improving and enhancing the standard for measuring the efficiency of the Network Intrusion Detection System (NIDS). The dataset provided here in KDD Cup 1999 contains a huge number of duplicate instances, which becomes too noisy during training of the machine learning model [12], [14], [26]. Because of this, NSL-KDD has an advantage, whereby most of the record duplication instances are considered as redundant and removed. The removal of such duplicated records leads to more optimized and refined data of the network traffic by increasing the capacity of evaluating the performance of NIDS.

There are 41 features in the NSL-KDD that were used as an ability to capture the characteristics of the network traffic. Some of these characteristics are certain connection details, timing details, the number of bytes that have been transferred and the actual payload content that has been transposed. These are in turn grouped in structural, content, time-based and host-based that aids in achieving enhanced statistical and machine-learning methods employed in intrusion detection. Therefore, the improvement over KDD-NSL concerning the reduction of loop redundancy and the balanced proportion of connections in different classes improves the ability to identify frequent and

infrequent attacks in NIDS [11], [15]. This type of dataset has been widely used in the research to develop and evaluate new algorithms and, therefore, this kind of dataset is more appropriate for the application of network security and the detection of intrusion.

## III. METHODOLOGY

### A. Model Initialization

K-Nearest Neighbor (KNN) is a nonparametric, supervised learning approach commonly used for classification and regression purposes. This occurs through identifying the 'k' closest points referred to as neighbors in the featured space compared to an input point. Moreover, it offers predictions either on the majority class in the case of classification or the averages of their values in case of regression. These distance metrics include Euclidean distance metrics, Manhattan distance metrics, Minkowski distance metrics as well.

KNN is particularly useful in detecting an anomaly as it can be seen to be accustomed to identifying data points that are far from the nearest neighbors of the given point. On the contrary, abnormal observations seem to have averagely or significantly fewer or a significantly higher number of neighbors compared to normal observations. KNN's are very handy, especially when it comes to handling multidimensional data and do not involve a lot of implementation complexities. That is; K= number of records in the training section analyzed to calculate the Euclidean distance for one record to all records in the training section and find a winner, K + 1= number of records stayed in the training section during the calculation of the distance between that record and all records in the training section and find the winner and member number of the record set of the training section.

$$\boldsymbol{d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}} \quad (1)$$

where,

d is the distance between two points x and y in an n-dimensional space.

The formula for calculating the anomaly score is given as:

$$Anomaly\ Score(x) = d\left(x, x_{(k)}\right) \quad (2)$$

where,

$x_{(k)}$ is the kth nearest neighbor of (x).

### B. Hyper parameter Configuration

Consequently, the aim of this study is to investigate the influence of learning rate and number of epochs on the accuracy of the WGAN-GP model. Therefore, the present research will feature plans to experiment with both of these two hyper parameters in an attempt to determine the impact of altering each of them on the required standards of the generated outputs. These are the learning rate that will also be altered to understand the effects it has when varied in its options, and number of epochs. The following is the summary of the hyper-parameters:

- Learning Rate: Determines change in weight per iteration and improves speed/stability of training.
- Num Epochs: Defines the number of times, for how many times the model is go to see the entire data while training.
- WGAN Data Augmentation Percentage: how much data is generated from the original data?

TABLE I. HYPER PARAMETER CONFIGURATION

| Total Instances | Learning Rate Range | Step Difference | Epoch Values | Augmentation Percentages |
|---|---|---|---|---|
| 48 | 1.00E-03 to 1.00E-01 | 9.10E-03 | 100, 150 | 30%, 50% |

### C. Evaluation Metrics and Qualitative Assessments

Both quantitative and qualitative approaches will be adopted in measuring performance as a means of having a balanced research outlook in the bid to establish the extent to which the model can create realistic synthesized data. In the present research context, Wasserstein Loss is one of the measures taken into consideration. It is used to measure the generative data, and it is core to the assessment of convergence of WGAN-GP with the actual data distribution. Another benefit of Wasserstein Loss is that compared to cross entropy loss, Wasserstein Loss provides a continuous gradient that helps a model steadily improve and generate many nearly realistic samples. As a result, this loss should be monitored to determine whether the model is learning and converging over time. The experiment's flow will be organized and conducted systematically in order to compare the effects of varying learning rate and epoch settings on WGAN-GP's performance accurately. To start with, the datasets that are to be used for training, which are NSL-KDD, will be preprocessed. After that, the training process will be taken over by varying the values of learning rate and number of epochs, and the model will be trained for each setting of both hyper parameters. In each iteration, the WGAN-GP model will work in turn to update both the discriminator and the generator [17], [18]. Every epoch contains several steps that include a discriminator to recognize sampled real and generated data, and update the generator based on this discriminator feedback. The above-described procedure of training will go on until the model is trained up to the possible maximum epochs or for a fixed epoch. It will then be conducted for all the selected learning-rate and epoch values in order to establish the relationship between these parameters and model's performances in producing realistic outputs.

The Classification Model Utility approach will be used to assess the model's performance after every training run. This approach is where the model is trained on the original data set while the other model is trained on the original and synthetic data set and both models are tested on the same validation set. A higher performance on the validation dataset proves the synthetic data's consistency and usefulness [29], [30]. This step will assist to detect flaws, for example, in the type of mode collapse, degenerate textures, or limited variation of the synthesized data produced. Adding these visual inspections to the quantitative measures will provide greater insight on the model's behavior and execution. After all the training runs have been performed, one will be able to compare the learn rate and epochs thus getting the needful and expected outcomes. This comparison will involve comparing the effects of altering the

hyper parameters in the performance of the adjusted model. The identification of trends in the quantitative metrics, coupled with the results of the visual inspections, will aid in determining the most appropriate learning rate and epochs to be used to prevent overfitting or insufficient training. This will be done numerically as well as in terms of the final generated samples to understand the impact of these hyper parameters when changing in WGAN-GP.

### D. Performance Metrics

The parameters applied on WGAN-GP for examining the performance are as follows:

Accuracy (ACC): It is considered as the most important parameter in evaluating the model's performance. This metric evaluates the quantity of number of samples that are correctly predicted over the number of all samples. The formula for calculating this metric is:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Recall: This parameter refers to the capability of the machine-learning model for predicting positive samples. It is calculated by dividing the number of samples that are categorized as true positive over all positive samples. The formula for calculating this metric is:

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

Precision: In this parameter, true positive identified number of samples over number of samples that are predicted as positive. The equation for calculating this metric is:

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

## IV. Experimental Results

In cyber threat detection the effectiveness of adaptive generative data augmentation is evaluated by a series of experiments, which were conducted on different augmentation series and training configurations. This study explores the impact on model performance occurs due to different settings of hyper parameters. Additionally, it focusses on generalization and optimization of the dynamics of model performance.

TABLE II. Performance Metrics of WGAN-GP Across Different Hyper parameter Configurations

| Performance Metrics | | | Hyper Parameter Configuration | | |
|---|---|---|---|---|---|
| **Accuracy** | **Precision** | **Recall** | **Learning Rate** | **EPOCH** | **Augmentation Percentage** |
| 0.856822 | 0.870409 | 0.85682183 | 1.00E-02 | 100 | 50.00% |
| 0.85297 | 0.855726 | 0.852969502 | 8.20E-02 | 150 | 50.00% |
| 0.815516 | 0.840894 | 0.815516319 | 2.80E-02 | 100 | 50.00% |
| 0.812413 | 0.812486 | 0.812413055 | 3.70E-02 | 150 | 50.00% |
| 0.74646 | 0.768186 | 0.746459782 | 3.70E-02 | 150 | 30.00% |
| 0.711932 | 0.79942 | 0.711931514 | 4.60E-02 | 100 | 50.00% |

Table II depicts the better performance on the specific hyper parameter configurations than the original dataset. It shows that out of 48 instances, the mentioned combinations have showed a significant increase in performance metrics as compared to the model performance on original dataset before the data augmentation. The data shown in Table II indicates the highest learning rate of 1.00E-02 at 100 epochs and 50% data augmentation, suggesting an optimal balance for model generalization.

Graphical presentation of these data is shown below in Fig. 3, which shows that the 50% augmentation covers a band while 30% augmentation shows a significantly lower recall which reinforces that model performances can be enhanced if sufficient data augmentation (50%) is used.

Fig. 4 suggests that training without proper learning rate may leads to diminish returns. The trend for recall also suggests the same and indicates optimal performance in 100 epochs with well optimized learning rate. As shown in Fig. 4, it is found that the highest level of accuracy is achieved at epoch for both levels of data augmentation. Following this, accuracy begins to deteriorate slightly, this indicates overfitting or the training has been carried out to the extent that the model is memorizing the set data instead of just learning. This occurs since, with a lot of training, the model is tasked with memorizing the training data and not learn general patterns that may occur in other real data [21].

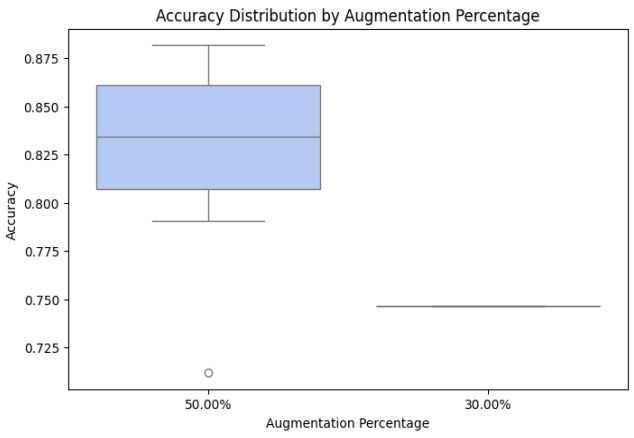


Fig. 3. Accuracy distribution by augmentation percentage.

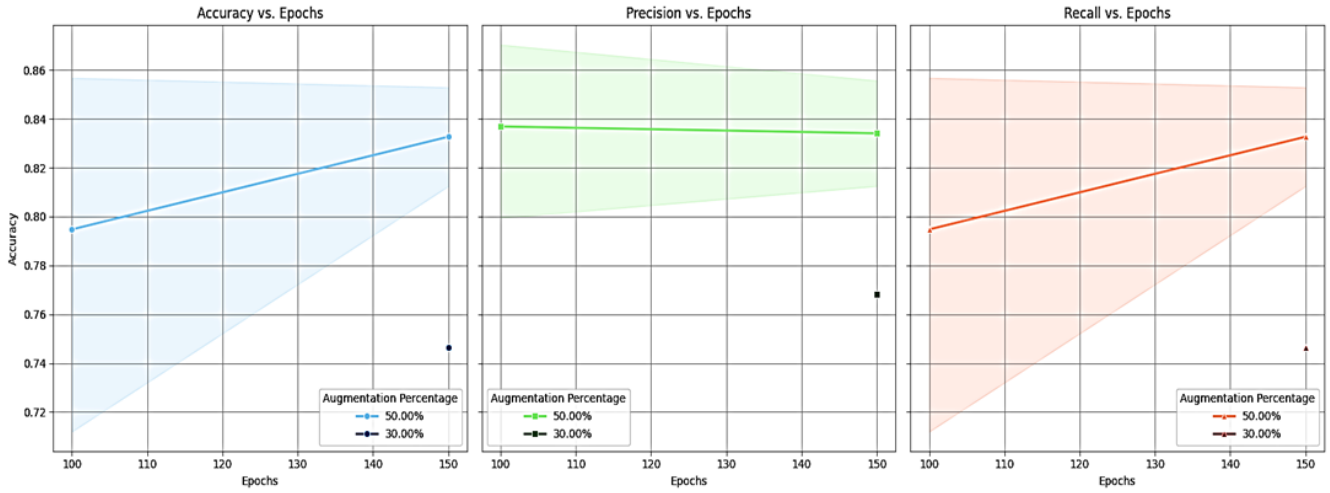


Fig. 4. Comparative view of accuracy, precision and recall with epochs.

As for configurations, the one of data augmentation equals to 50% provides better results in most cases in terms of accuracy compared to 30% augmentation. What this entails is that inputting a broader and comprehensive variety of augmented data aids in the model's performance in terms of generalization. Even when it comes to precision, the aim of having 50% of servings augmented is seen to be the best. As can be noticed, precision does not decrease with time, and therefore, it is stable in different epochs. This implies that a reduced 50% augmented model yields a fewer number of false positive as compared to the 30% augmented model. Fewer false positive means that the model is correctly segregating between relevant and irrelevant samples which is extremely important when the classification is done, and leads to certain results [20].

A higher level of dispersion in the accuracy values is noted as shown in Fig. 5 and Fig. 6, which suggests variability in the performance of models in the different configurations. The median has been increased compared to the 30 percent augmentation result which affirms the benefits of incrementing the augmentation percent. Nonetheless, there are a few points with the accuracy below the average, which indicates that the higher level of augmentation does not have as a positive effect on certain configurations. Nevertheless, a majority of the accuracy values have a higher stage, which provides evidence that 50 percent augmentation ratio still helps to enrich the model.

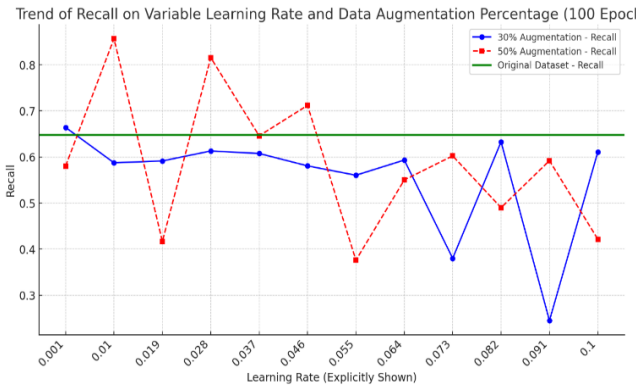


Fig. 5. Trends of Accuracy on variable learning rate and data augmentation with 100 epochs.

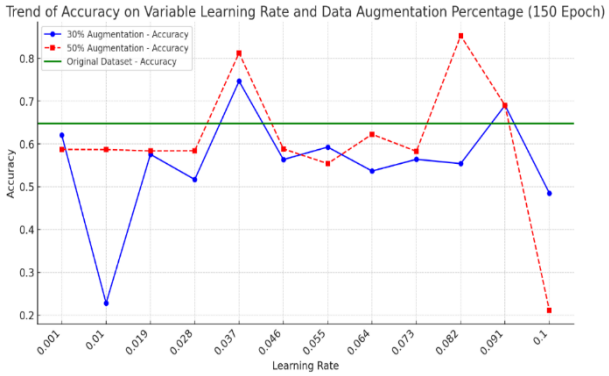


Fig. 6. Trend of accuracy on variable learning rate and data augmentation with 150 epoch.

From Fig. 5 and Fig. 6, the accuracy for 30% augmentation is lower compared to the previous results, which indicates less efficiency. Therefore, all the estimated accuracy values are less than in the 50% augmentation scenario. The box plot shows the minimal variation, proving that lower levels of augmentation only bring a marginal improvement in performance. In this case, the fact that there are few changes foretells that an augmentation by 30% does not lead to enhancing the model's ability to generalize or its robustness.

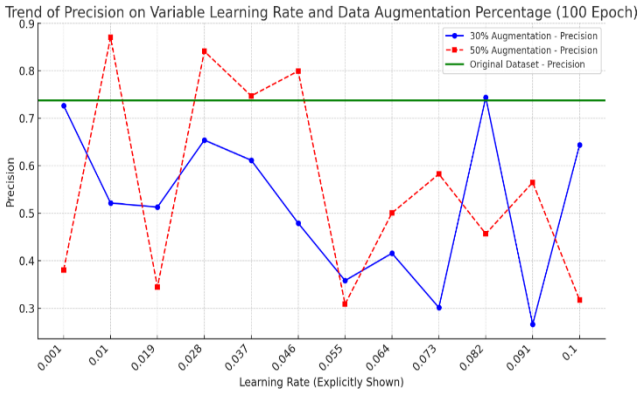


Fig. 7. Trend of precision in variable learning arte and data augmentation with 100 epoch.

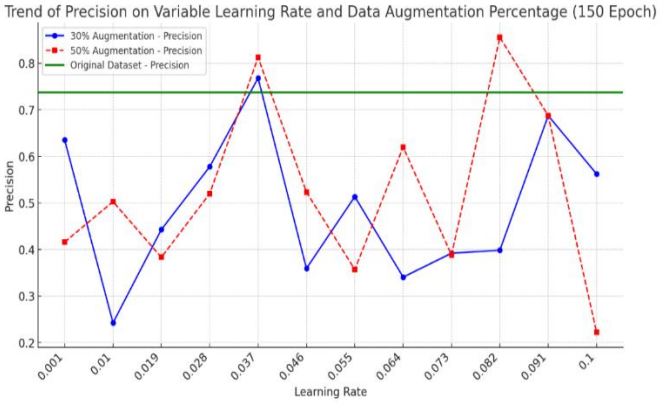


Fig. 8. Trend of Precision on variable learning rate and data augmentation with 150 epoch.

Fig. 7, and Fig. 8, present the trend of precision for various learning rates and augmentation levels of data (30% and 50%) with two specific epoch values. A drop at a learning rate of 0.053 indicates an unstable zone where performance drops in the model. The instability possibly stems from poor convergence or too much weight update, causing non-optimal learning. As the learning rate diverges from this unstable region, accuracy becomes stable, illustrating the significance of having a suitable learning rate.

In 100 Epochs, Fig. 9, recall for a 50% increase in most learning speeds, except for a noticeable peak of 0.082, is still relatively stable. This suggests that the medium learning speeds combined with high growth levels help the model maintain more positive examples. In contrast, a 30% increase shows more fluctuations, sharp falls of 0.01 and a gradual medieval recovery (0.046 to 0.082). Increased volatility at low growth levels indicates that insufficient data text affects the model's ability to normalize. With a high teaching rate (0.1), recall means both growth percentages, indicating the model's instability. In 150 Epochs, Fig, 10, the recall is improved and is stable compared to 100 epochs, reflecting the benefits of extended training. Extending the training period to 150 epochs, as depicted in Fig. 10, results not only in an enhancement in recall performance, but also significantly sharpens the consistency relative to the scenario with 100 epochs.

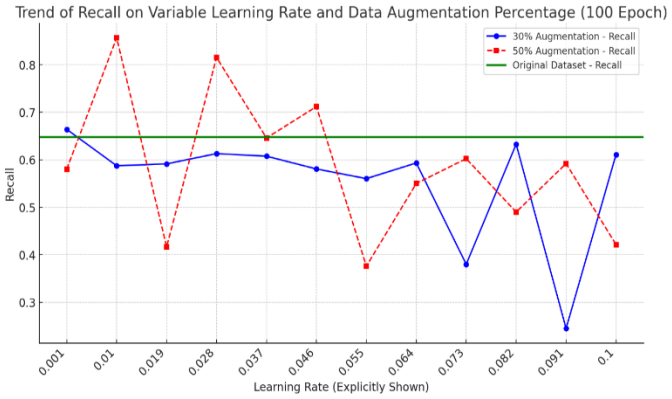


Fig. 9. Trend of recall on variable learning rate and data augmentation percentage with epoch 100.

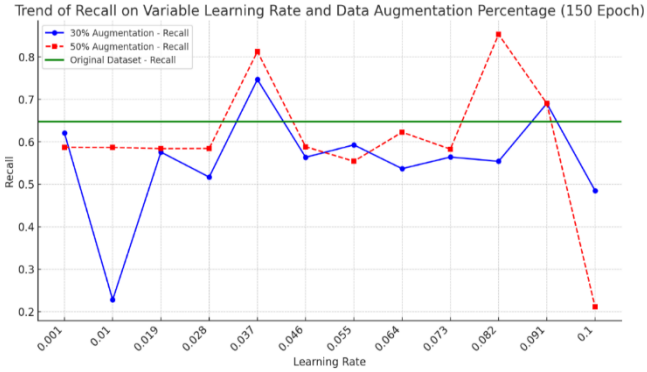


Fig. 10. Trend of recall on variable learning rate and data augmentation percentage with epoch 150.

## V. Discussion

The interaction among learning rates, epoch numbers, and levels of data augmentation is important to get a better understanding of the research objective. The results presented in the above section provided deeper insights into the behavior of the model under diverse training scenarios.

As shown in F II, some hyper parameter settings perform much better than the model trained on the original dataset alone without augmentation; of 48 instances tested, some combinations, especially those using more data and learning rates fine-tuned, showed significant improvement in performance. Specifically, the setup with a learning rate of 1.00E-02, 100 epochs of training, and 50% data augmentation produced the most beneficial outcomes, which suggests the best balance between training depth and model generalization. These findings further stress the need for well-chosen training parameters in improving the capability of the model to learn from and accommodate more varied data.

In cyber threat detection, an effective combination of moderate learning rate, controlled epochs and higher augmentation is crucial for optimization. In terms of accuracy and precision, the trend suggests that 100 epochs yield better performance than 150 epochs when paired with optimize learning rate.

The efficiency of the model is enhanced when trained for 150 epochs compared to 100 epochs to prove the model learnt sufficiently more epochs as training epochs increases. Further on in training, another important characteristic of the model develops in that the model is able to comprehend more complex patterns and representations, thus the accuracy, precision and recall will be improved. This means that the differences between 30% and 50% augmentation are as follows: The readers are as follows: But it was also observed that both augmentation percentages improve with an increase in training time, while 50% augmentation performs better than 30% augmentation in most cases, which ends the thought that higher synthetic data helps in improving the generalization of the model. Further, for all the evaluation criteria and epochs as well as augmentation level, it is found that all the Q-Learning rates in the mid-range categorized between 0.037 and 0.082 are the best performing one. These discoveries show that there is a factor of the training period and rate to be considered in order to achieve the best performance of the model. There is an improvement in all of the

metrics, accuracy, precision and recall, if 50% is augmented instead of 30%. The fact that more augmentation allows for the creation of more various samples in the synthetic data, decreases overfitting and increases generalization of the model when it is trained on it. The improvement is most significant at a moderate learning rate, where the augmented data is valuable in providing the model with the right guiding patterns without the inclusion of noises. This means that in this particular dataset and for this particular task, a higher level of augmentation is beneficial on the model. As indicated, the learning rates between 0.037 and 0.082 are suitable for the high augmentation level and overall, provide the best results. These values determine the trade-off of fast convergence or stable convergence in a learning process. Too small learning rates such as 0.001 to 0.01 make the learning slow and ineffective, mostly due to slow convergence. Taking such small steps means that the model may take too long in order to learn meaningful features during the training phase which results in poor performance even when the number of iterations is increased. However, if the learning rate = 0.1, this causes instability and degradation of the performance. It stirs difficulty to reach nadir solution, as large update alters the weights radically, resulting in impulsive degradation of accuracy, precision and recall. This goes to support the argument that the learning rate should be properly selected and small to large values should be avoided, while small to large values could take a long time to converge and are somewhat unstable. The model tested for 150 time passes through the training set and, therefore, it demonstrates an increase in its performance that should be emphasized as a result of protracted training, particularly for large sets. More training iterations enable the model to perform very effectively in analyzing and identifying patterns in the data and thus increases the accuracy, precisions, and recall. However, as it has been demonstrated, more sophisticated training aids in the improvement of the learning rates but their tuning is still essential in order to avoid overfitting as well as instability. Selecting a bad learning rate, even if training is conducted for a long time, can have a negative impact on the performance. Consequently, it was identified that to obtain the best performance, the number of epochs must be at least 150 along with the best learning rate. Accuracy, precision, and recall exhibit similar trends across different learning rates, augmentation levels, and epoch counts. This ensures the accuracy of the analysis as it shows that the changes are not arbitrary but due to the model's response to various conditions. This fact implies that the model performs well across all three metrics because there is no extreme focus on one of the metrics while ignoring the other two. From the above analysis, it can be recommended that the following measures should be taken in order to enhance the performance of a model. First, a 50% of augmentation should be applied to decrease the model variance and subsequently improve generalization to all the metrics. Secondly the learning rate should be chosen in a certain range 0.037 to 0.082 in order to decrease speed of convergence and increase stability. Lastly, training should be carried out to the 150-epoch level in order to achieve the best results, especially where there is large data or complicated structures. That being said, the following recommendations will develop better performing workflow while keeping it stable and efficient to an extent.

Therefore, based on accuracy, precision, and recall, 50% augmentation is better than 30 % augmentation. The higher level of the data augmentation brings more diversified data samples that increase the ability of the model to generalize. This is very well illustrated in the convergence which shows that for all the epochs, 50% augmentation provides higher scores than models trained with other levels of augmentation. Also, it can be seen that standard deviations in 50% augmentation are distributed over a wider range showing more versatility that can be advantageous in practical applications across different settings. The other benefit that could easily be observed in the implementation of 50% augmentation is enhanced recall. As recall is about the model's ability to identify all required cases, the improvement indicates that a higher augmentation level includes more relevant changes in the training data [24]. Consequently, the model becomes better at recognizing positive cases as well as does not overlook any vital patterns. This will prove helpful in situations where the false negatives are debilitating, for example, in medical diagnosis or checks on fraudulent individuals. On the other hand, the increased ratio of just 30% does not seem to give the model a large enough variety of samples to learn adequately. Overall, the augmentation percentage is generally below what is obtained with a 50% augmentation number. Additionally, referring to entropy analysis and the trends in precision and recall, it can be concluded that the increase does not exceed 30% and thus cannot produce enough variation in order to achieve higher results. This shows that the model trained with 30% augmentation might have a difficulty in learning proper representations that can generalize well. However, the lower recall and precision observed in 30% augmentation suggest that the model is more error-prone. As shown from the results, the model entails lesser parameters hence, it fails to capture a large amount of data, which leads to higher percentage of false negatives, and it also has fewer capabilities of classifying relevant data from irrelevant data. Such issues indicate that 30% augmentation may not be the optimum solution for applications that require high reliability. Another noteworthy discovery revealed in this comparison is that precision is steady even as the epochs increase for 50% augmentation. It is clear from the above findings that the precision rate is still higher in models that have been trained with an augmentation of 50% as compared to that of 30%. This means that the model is more accurate in avoiding false positives which are very important in real-life scenarios due to the impact of wrong classification [25], [27].

In overall the result of every epoch shows that by increasing augmentation percentage, the precision rate is also more stabilized. The recall values also are exhibited in the same manner as accuracy. Thus, the performance scores for recall in both augmentation levels initially rises and after that reduces from the epoch of training. As it may be inferred, a higher augmentation percentage increases that kind of performance, but that extensive epochs diminish the ability to correctly classify positive samples. Hence, the results suggesting that recall of 50% was obtained with 50% augmentation supports the point about appropriate augmentation resulting in improved sampling of the whole population. Considering the accuracy, precision, and recall trends over time, it is clear that precision is a relatively stable metric where values fluctuate the least, although settings such as the '50% augmentation setting' show marginal downs

and ups. Both accuracy and recall present some of the fluctuation though, whereas, the precision has ameliorated more or less in a general improved trend. This stability also shows the advantage of using a higher augmentation percentage because the models over emphasizing does not deteriorate such aspects [23], [28]. However, it is crucial to remember that after certain epoch level, the accuracy and recall become less efficient, which again reflects that there are more other steps such as early stopping to prevent overfitting. These three factors offer significant insight into the best setup for model training. The first important conclusion is that the increase of the number of samples by 50% also increases precision because it is the ratio of accurately identified positive cases. The study also notes that there is a tendency to overfit the training data when the epochs are trained beyond the threshold value. After this point, both recall and accuracy surface as having a decreased rate, which indicates that the oversimplification of training is detrimental. It is noted that this situation calls for either the use of early stopping techniques or the learning rate changes for the best results.

The evaluation based on Fig. 5 and Fig. 6, suggests that 50% augmentation is better in terms of median accuracy and variability as the method deploys fewer units at once but has a higher potential by maintaining precision across various configurations. The variability of accuracy seems to go up, and it means that higher levels of augmentation aid in enhancing the model's flexibility. On the other hand, a narrower range of accuracy in the 30% augmentation scenario also suggests that the augmentation is not very effective in enhancing the generality and stability of performance. Therefore, the use of 50% augmentation can also be seen to be more effective in improving the performance of the models than 30% augmentation.

The analysis of recall performance within various learning rates and data growth factors for different training durations offers important understanding into the characteristics and stability of the WGAN-GP model. Recall, for the most part, remains stable in the 50% data growth mark for most learning rates with a peak at 0.082. This is especially the case for intermediate learning rates, which appear to be more favorable when combined with higher data availability, as the model's ability to recall and recognize salient examples improves. In comparison, the volatile recall performance at a 30% growth rate, with sharp subtractive spikes down 0.01 and gradual gains between 0.046 and 0.082, suggests that lower data growth levels might be inefficient, where insufficient training signals might hinder model generalizing and normalizing ability. Additionally, extreme learning rates, such as 0.1, invoke unstable recall at both growth percentages, highlighting the issue of structured adaptation under extreme learning conditions.

Higher levels of data augmentation also enhance generalization, minimizing overfitting and increasing robustness. Between the two augmentation approaches, 50% augmentation uniformly produces better accuracy at most learning rates and hence is the model of choice for stability and effectiveness of the model. From Fig. 9, and Fig. 10, the 50% increase improves an increase of 30% at all learning speeds continuously, strengthening the efficiency of improving the models' ability to capture positive examples. The best recall performance is seen in mid -range learning speeds (0.046 to 0.082), and corresponds to trends seen in accuracy and learning. However, recalling is still experiencing a sharp decline in the highest learning frequency (0.1) similar to other performance matrix. This further emphasizes that models prevent very high learning speeds instead of increasing performance.

## VI. Conclusion

In order to identify the best hyper parameter configurations for reliable and effective training, this study methodically investigates the effects of learning rate, epoch count, and data augmentation percentage on the performance of WGAN-GP models. This study highlights that excessively low learning rates slow convergence and result in suboptimal model performance, while high learning rates can lead to mode collapse and unstable training dynamics. It does this by examining a range of learning rates and determining the crucial balance between training stability and convergence efficiency. The study also explores how data augmentation can improve sample diversity and generalization, showing that while excessive augmentation introduces noise and reduces the fidelity of generated data, moderate augmentation improves the model's capacity to generalize. In order to identify the ideal point at which further training stops improving sample quality or results in overfitting, the impact of epoch count on model performance is also evaluated. Maximizing the representation capacity of WGAN-GP models requires finding the ideal balance between under-fitting and overfitting. Deeper understanding of stability, mode collapse, convergence rates, and the general fidelity of generated data can be gained by comparing various training configurations in the future studies. This study also emphasizes the need for integrated hyper parameter tuning because learning rate, augmentation, and epoch count all affect training dynamics. The results provide specific suggestions for choosing the best hyper parameters, guaranteeing that WGAN-GP models produce output of higher quality with increased stability and effectiveness. In real-world use cases, including healthcare, finance, and autonomous systems, stability and adaptability are as important as high accuracy. This 50% augmentation level combined with tuned hyper parameters seems to be a suitable solution for optimized performance with any configuration. By establishing best practices for tuning WGAN-GP, this study provides a structured approach for optimization of hyper-parameters, offering a robust framework for training diverse data domains in generative models.

Even with the insightful findings of this research, there are a number of limitations that must be noted. The analysis was based on a limited set of learning rates, epochs, and augmentation levels, which might not completely represent the behavior of WGAN-GP models on different datasets or more sophisticated data domains. Moreover, the research was based on traditional augmentation methods, excluding more sophisticated options like synthetic sample creation or domain-specific transformations that might have had varying results. The hyper parameter tuning was similarly performed manually without using automated optimization methods like grid search or Bayesian optimization, which may provide more accurate configurations. These constraints points to the necessity of wider experimentation and more adaptive tuning approaches in

subsequent research to further improve the generalizability and stability of WGAN-GP models.

Future studies should similarly compare more varying augmentation levels in order to find out if there is any improvement. Moreover, future explorations should focus on more sophisticated augmentation approaches like: generating synthetic samples, and geometric transformations, that ideally could improve both adaptability and stability of the models when trained on various datasets. The learning rate determines speed at which the model travels through the learning space and hence, correct setting of this factor is important so that the model does not oscillate uncontrollably. Advanced variations like grid search or Bayesian optimization should be employed in future studies to determine the suitable learning rate that would enable fast convergence while at the same time avoiding premature convergence.

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# Adaptive Crow Search Algorithm for Hierarchical Clustering in Internet of Things-Enabled Wireless Sensor Networks

Lingwei WANG, Hua WANG*
Guangdong University of Science and Technology, Dongguan, Guangdong, 523083, China

***Abstract*—The Internet of Things (IoT) relies on efficient Wireless Sensor Networks (WSNs) for data collection and transmission in various applications, including smart cities, industrial automation, and environmental monitoring. Clustering is a fundamental technique for structuring WSNs hierarchically, enabling load balancing, reducing energy consumption, and extending network lifespan. However, clustering optimization in WSNs is an NP-hard problem, necessitating heuristic and metaheuristic approaches. This study introduces an Adaptive Crow Search Algorithm (A-CSA) for clustering in IoT-enabled WSNs, addressing the inherent limitations of the standard CSA, such as premature convergence and local optima entrapment. The proposed A-CSA incorporates three key enhancements: 1) a dynamic awareness probability to improve global search efficiency during initial population selection, 2) a systematic leader selection mechanism to enhance exploitation and avoid random selection bias, and 3) an adaptive local search strategy to refine cluster formation. Performance evaluations conducted under varying network configurations, including node density, network size, and base station positioning, demonstrate that A-CSA outperforms existing clustering approaches in terms of energy efficiency, network longevity, and data transmission reliability. The results highlight the potential of A-CSA as a robust optimization technique for clustering in IoT-driven WSN environments.**

***Keywords*—Internet of things; wireless sensor networks; clustering; energy efficiency; optimization**

## I. Introduction

### A. Background and Motivation

The rapid expansion of the Internet of Things (IoT) has driven the widespread deployment of Wireless Sensor Networks (WSNs) for real-time data collection and communication in diverse applications [1]. Recently, WSNs have been extensively used in different sectors since they are affordable and easy to set up [2]. WSN comprises several diminutive Sensor Nodes (SNs) with restricted power supplies placed in surveillance regions to gather environmental information, including humidity, temperature, pressure, vibrations, and other characteristics [3]. The data is collected by combining many wireless connections and sent to a central station for assessment and processing [4].

Data transmission is the primary source of energy consumption in WSNs. SNs dissipate significant amounts of energy as packets of data are sent from one end of the network to the other. SNs are at risk of running out of energy while sending data packets owing to their low battery capacity. This issue can lead to premature network failure [5]. If not resolved, it poses a significant danger to the longevity of these networks. Reducing the size of data packets exchanged between SNs and finding the best routes for transmitting these packets are effective methods of managing energy usage in WSNs, resulting in enhanced and prolonged network functionality [6].

### B. Research Problem and Challenges

WSNs trace their roots back to the "Tropical Tree" sensor system employed in the Vietnam War. Shahraki, et al. [7], introduced a novel algorithm that synergizes clustering strategies with compressed sensing, providing formal proofs for optimal cluster size, Cluster Head (CH) distribution, and inter-layer relationships. This approach effectively mitigates "hot issues" and curbs energy consumption arising from frequent CH role rotations. Recent advancements in low-power communication and signal processing technologies have facilitated widespread WSN deployment.

While cluster formation and CH selection are fundamental to WSNs, traditional protocols like LEACH and its centralized variant face limitations due to increasing network demands [8]. As WSNs are primarily battery-powered with dynamic topologies and unfixed node IDs, specialized routing protocols are imperative [9]. Clustering algorithms divide the network into manageable clusters. Network longevity relies on efficient energy management, and routing protocols have evolved accordingly [10].

In parallel with these developments, cross-disciplinary advancements have further enriched the analytical frameworks supporting WSNs. For instance, machine learning techniques have been employed to model and predict system behavior under complex environmental and economic variables, offering insights into adaptive strategies for WSN optimization [11]. Similarly, advanced simulation models, such as those used for weak rock mass behavior, demonstrate the importance of integrating environmental variability into system design and reliability assessments [12].

### C. Authors' Contribution

This paper introduces a novel clustering protocol based on the Adaptive Crow Search Algorithm (A-CSA). This study seeks to answer the central question: How can the basic CSA be enhanced through dynamic parameter tuning, structured leader selection, and adaptive local search to improve energy-

efficient clustering and prolong network lifetime in IoT-enabled WSNs?

To alleviate the energy consumption burden on Cluster Heads (CHs), we propose a relay node-assisted approach. Each CH is assigned a dedicated Relay Node (RN), eliminating the need for CHs to select next-hop nodes and reducing channel contention. RN selection is based on available energy, distance to the Base Station (BS), and proximity to the CH. To optimize CH and RN selection, we formulate a bi-objective fitness function that considers node position and residual energy. Given the NP-hard nature of this problem, A-CSA is employed to derive optimal solutions efficiently.

The body of the paper is formatted in the following way. A review of related work in WSN clustering and metaheuristic algorithms is presented in Section II, summarizing key developments and challenges. System model, network architecture, and energy considerations are explained in Section III. Section IV describes the clustering approach in detail. Section V discusses the enhanced CS algorithm for cluster node updating. Simulated results are presented in Section VI. The paper concludes with a summary and suggestions for further research in Section VII.

## II. Literature Review

An overview of clustering and optimization protocols in WSNs is provided in this section. A comparison of metaheuristic and hybrid optimization techniques is presented in Table I, highlighting the key contributions of different approaches, algorithms, and performance metrics.

Chandirasekaran and Jayabarathi [13], developed a novel WSN protocol that leverages the Cat Swarm Optimization (CSO) algorithm for real-time clustering. Their approach minimizes distances within the cluster and optimizes energy distribution. By considering received signal strength, remaining battery voltage, and distance within the cluster, CSO effectively selects CHs. Performance evaluations against LEACH-C and PSO showed significantly improved battery life compared to traditional methods.

Mehta and Saxena [14], suggested a novel clustering and routing approach for WSNs using Sailfish Optimizer (SFO) to improve energy efficiency. A multi-objective fitness function guides the selection of CHs, prioritizing energy conservation and minimizing node failures. SFO determines optimal data transmission paths to the sink node. A comparative analysis of GWO, GA, ALO, and PSO shows superior performance for energy consumption and network lifespan, with corresponding improvements of 21% and 24% over GWO, respectively.

Nabavi, et al. [15], offered a novel hybrid approach to optimizing WSNs, combining genetic and Gravitational Search (GS) algorithms. The genetic algorithm was employed for CH selection, aiming to minimize intra-cluster distances and energy consumption, while GS was utilized for efficient routing between CHs and the sink node. The proposed technique demonstrated superior efficiency regarding energy efficiency, network throughput, and data delivery rate compared to existing techniques.

TABLE I Studies on Clustering and Optimization Strategies in WSNs

| Study | Algorithm(s) used | Contribution | Performance metrics | Shortcoming |
|---|---|---|---|---|
| [13] | Cat swarm optimization | Real-time clustering, minimizing intra-cluster distances, and optimizing energy distribution | Improved battery life | Premature convergence, lacks adaptive search mechanism |
| [14] | Sailfish optimizer | Multi-objective CH selection and optimal data transmission paths | Energy consumption and network lifespan | High computational complexity, lacks relay node optimization |
| [15] | Genetic and gravitational search algorithms | Hybrid approach for CH selection and efficient routing | Energy efficiency, network throughput, and data delivery rate | Increased computational overhead, no adaptive clustering strategy |
| [16] | Ant colony optimization and butterfly optimization algorithms | Energy-efficient clustering with mobile sink option to mitigate hotspot problem | Residual energy, throughput, and alive nodes | High convergence time, lacks adaptive exploration-exploitation balance |
| [17] | Differential evolution and sparrow search algorithms | Hybrid approach for energy-efficient CH selection | Network lifespan, residual energy, and throughput | Susceptible to local optima, lacks adaptive parameter tuning |
| [18] | Levy chaotic particle swarm optimization | Enhanced convergence and search space in cluster routing, focusing on realistic industrial conditions | Energy usage and network longevity | Lacks adaptive control over search balance |
| [19] | Capuchin search algorithm and fuzzy logic | Energy-efficient data aggregation with multi-phase cluster formation and routing | Energy usage, delay, packet delivery rate, and network lifespan | Complexity in multi-phase processing, no dynamic relay node selection |
| [20] | Fuzzy logic and quantum annealing | On-demand clustering and energy-efficient routing to extend WSN durability | Network lifetime, energy consumption, and throughput | Computational complexity and dependency on predefined thresholds |

Amutha, et al. [16], developed a novel energy-efficient clustering algorithm for WSNs that combines Ant Colony Optimization (ACO) and Butterfly Optimization (BO) algorithms. BO is employed for optimal CH determination, while ACO is used for energy-aware routing. To further extend network lifespan, two variants are introduced: HBACS with a fixed sink and HBACM with a mobile sink. The latter mitigates the hotspot problem by eliminating multi-hop communication between CHs and the sink. Simulation results with NS2 show significant improvements in residual energy, active nodes, and throughput for both variants compared to conventional algorithms.

Kathiroli and Selvadurai [17], suggested a hybrid optimization approach combining Differential Evolution (DE) and Sparrow Search Algorithm (SSA) to enhance energy efficiency in WSNs through optimized CH selection. Leveraging SSA's global search capability and DE's local search potential, the proposed algorithm effectively extends the network lifetime. Evaluation metrics include residual energy, network lifetime, throughput. Compared to existing methods, the hybrid SSA-DE approach demonstrated improved residual energy and throughput, highlighting its effectiveness in selecting optimal CHs.

Luo, et al. [18], developed an enhanced Levy Chaotic Particle Swarm Optimization-based Cluster Routing Protocol (LCPSO-CRP) for extending WSN lifetime. By introducing a chaotic optimization methodology, the protocol significantly accelerates convergence and expands the range of possible solutions. This innovative strategy, in accordance with BS distance, cluster-to-cluster distance, and node energy levels, outperforms traditional schemes like DEEC, LEACH, LEACH-kmeans, and LEACH-C. Extensive simulations under realistic industrial conditions demonstrate a minimum 22.9% reduction in energy consumption and a 13.9% extension of network longevity for LCPSO-CRP.

Mohseni, et al. [19], proposed a novel energy-efficient data aggregation routing mechanism for WSNs that couples the Capuchin Search Algorithm (CapSA) and fuzzy logic operators. This multi-phase approach comprises two primary steps: cluster creation and internal/external routing. Simulations using MATLAB validate the superiority of the suggested design regarding energy usage, delay, packet delivery rate, and network lifespan compared to existing approaches.

Wang, et al. [20], designed a hybrid routing and clustering protocol (FQA) combining fuzzy logic and quantum annealing to maximize WSN durability and decrease energy usage. Fuzzy logic is employed for intelligent CH selection, while quantum annealing optimizes data routing to the BS. An energy threshold mechanism is incorporated to expedite the process. Unlike traditional periodic clustering, FQA adopts an on-demand approach to reduce computational overhead. Comparative analysis against FC-RBAT, OAFS-IMFO, BOA-ACO, and FRNSEER consistently demonstrates FQA's better performance by demonstrating better network lifespan, data transfer rate, and energy usage across various scenarios.

Existing clustering and optimization techniques for WSNs have demonstrated notable improvements in energy efficiency, network lifespan, and data transmission reliability. However, several challenges remain unaddressed. Many approaches, including those based on CSO, SFO, and hybrid metaheuristic techniques, suffer from premature convergence, leading to suboptimal CH selection and inefficient energy distribution. Additionally, while hybrid methods enhance solution quality by leveraging multiple algorithms, they often introduce excessive computational overhead, making them less practical for real-time WSN applications.

Some techniques, such as those using fuzzy logic or chaotic optimization, improve network longevity but lack adaptability to dynamic network conditions. Furthermore, relay node selection remains an overlooked aspect, with most studies focusing solely on CH selection without optimizing multi-hop communication. To address these limitations, our proposed algorithm introduces dynamic awareness probability, systematic leader selection, and adaptive local search, ensuring balanced exploration and exploitation while enhancing clustering efficiency and energy management in IoT-driven WSNs.

## III. System Model

For real-time environmental monitoring, a WSN of $N$ SNs is considered. As shown in Fig. 1, each SN is equipped with a microcontroller unit, a communication unit, and a power management unit. SNs exhibit identical capabilities to operate in sensing or communication modes, collecting environmental data or transmitting information, respectively. Each SN possesses a data link to handle all data traffic. Nodes are spatially indexed. Static network topology is assumed to be consistent with typical WSN deployments. Table II summarizes the symbols and their definitions used in whole body of the study.

SNs are initialized with equal energy levels, creating a homogeneous network. It is impossible to replace the battery, simulating unattended operation. Environmental data are collected at fixed intervals and transmitted periodically. SNs can adjust transmission power across multiple levels based on recipient distance. Bidirectional communication links exist between nodes, with distance estimation relying solely on received signal strength. Exploiting data correlation, CHs compress gathered data into fixed-length packets. The BS maintains a continuous power supply.

This study adopts a simplified communication energy consumption model incorporating path loss effects, as illustrated in Fig. 1. The propagation channel is characterized by either free space (inverse square law) or multipath fading (inverse fourth power law) attenuation, contingent upon transmitter-receiver distance. Power control mitigates these losses. For distances below a threshold, $d_0$, free space propagation is assumed; otherwise, the multipath model prevails.

TABLE II SYMBOLS AND DEFINITIONS

| Symbol | Definition | Symbol | Definition |
|---|---|---|---|
| $N$ | Number of sensor nodes | $d_0$ | Threshold distance for free-space vs. multipath propagation |
| $K$ | Data packet size | $E_{TX}$ | Transmission energy consumption |
| $d$ | Transmission distance between nodes | $E_{elec}$ | Circuit energy dissipation per bit |
| $E_{RX}$ | Reception energy consumption | $E_{fs}$ | Free-space model amplifier energy |
| $E_{mp}$ | Multipath fading model amplifier energy | $k$ | Number of active (operational) nodes at a given time |
| $\xi$ | Predefined threshold for the proportion of dead nodes | $FND$ | Time until the first sensor node depletes its energy |
| $PND$ | Time until a specified proportion of nodes are dead | $\overline{CH}$ | Set of non-CH nodes |
| $n$ | Number of clusters formed | $R_{energy}^{CH}$ | CH energy ratio relative to non-CH nodes |
| $F_{CH}$ | Fitness function for CH selection | $R_{location}^{CH}$ | CH location ratio relative to non-CH nodes |
| $E_{CH}^{res}(j)$ | Residual energy of CH node j | $a$ | Weighting factor for fitness components |
| $\bar{E}_{CH}$ | Average residual energy of CHs | $\bar{D}_{CH}$ | Average distance of CHs from the BS |
| $\bar{L}_{CN}$ | Average distance of CNs from BS and CHs | $F_{RN}$ | Fitness function for relay node selection |
| $x_{i,t}$ | Position of crow $i$ at time $t$ | $m_{i,t}$ | Memory position of crow $i$ at time $t$ |
| $fl$ | Flight length factor | $K_t$ | Dynamic awareness probability at generation t |
| $K_{max}$ | Maximum awareness probability | $K_{min}$ | Minimum awareness probability |
| $t_{max}$ | Maximum number of generations | $AP$ | Awareness probability |
| $D_{thr}$ | Threshold distance for adaptive flight length | $gb_{j,t}$ | Best position of crow $j$ at time $t$ |

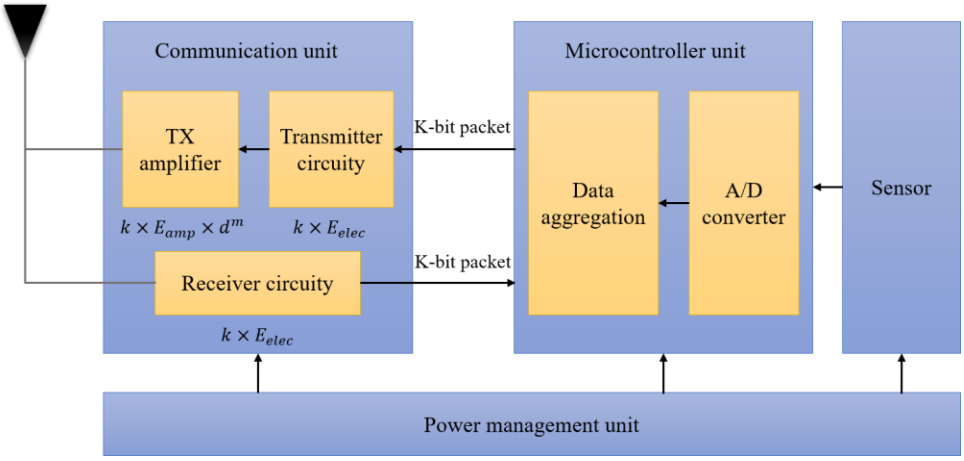


Fig. 1. Components and configuration of SNs in WSNs.

Eq. (1) quantifies the energy expended in relaying a *K-bit* packet across a distance *d*. The components of this energy consumption model include transmission energy ($E_{TX}$), reception energy ($E_{fs}$), link distance ($d$), circuit-level energy dissipation ($E_{elec}$), amplifier model parameters ($E_{fs}$, $E_{mp}$), data packet length ($k$), and the transmission distance threshold ($d_0$) defined in Eq. (2). Eq. (3) determines packet reception energy consumption. $E_{elec}$ encompasses the energy consumed by transmitter or receiver circuitry, influenced by factors such as signal spreading, filtering, modulation, and channel coding.

$$E_{TX}(k,d) = \begin{cases} k \times E_{elec} + k \times E_{fs} \times d^2 & if\ d \le d_0 \\ k \times E_{elec} + k \times E_{mp} \times d^4 & if\ d > d_0 \end{cases} \quad (1)$$

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \quad (2)$$

$$E_{RX}(k) = k \times E_{elec} \quad (3)$$

The resilience of many WSN applications to node failures is evident, particularly in high-density deployments where redundant sensing capabilities exist among neighboring nodes. Consequently, the duration before First Node Dead (FND) is an insufficient metric for comprehensive network lifetime assessment. A more robust indicator, the time until a predefined percentage of nodes dead (PND), is proposed for scenarios characterized by high node density. Eq. (4) defines network lifetime as the duration before the proportion of operational nodes reaches a specified threshold, $\xi$. Within this equation, $N$ denotes sensor count and $k$ signifies the number of active nodes.

$$T_N^k = T\left[\xi = \frac{k}{N}\right] \quad (4)$$

## IV. CLUSTERING APPROACH

The proposed protocol categorizes nodes into CHs, Common Nodes (CNs), and RNs. Network configuration comprises repeated cluster formation and data transmission stages. During the setup phase, clusters, CHs, RNs, and routing paths to the BS are established. The data transmission phase involves data collection by CHs from cluster members, relayed

through RNs to the BS, following a predefined scheme. Fig. 2 illustrates the network architecture.

Given *N* randomly deployed SNs, *n* clusters are formed. The set of CHs is denoted as CH, while non-CH nodes are represented by $\widetilde{CH}$ . CHs coordinate cluster operations, aggregate data, and communicate with RNs. CH selection considers node energy levels and locations, prioritizing nodes with more available energy and closer to the BS for balanced cluster formation. This optimization problem is formulated in Eq. (5).

$$F_{CH} = a \times R_{energy}^{CH} + (1 - a) \times R_{location}^{CH} \quad (5)$$

The fitness function, $F_{CH}$, comprises two components: $R_{energy}^{CH}$ and $R_{location}^{CH}$, weighted by $\alpha$. $R_{energy}^{CH}$, calculated in Eq. (6), represents CH energy relative to non-CH energy, favoring energy-rich nodes as CHs. $R_{location}^{CH}$, determined by Eq. (7), measures the relative distance of CHs and non-CHs to the BS, promoting CHs closer to the BS for improved energy efficiency.

$$R_{energy}^{CH} = \frac{\bar{E}_{CH}}{\bar{E}_{\widetilde{CH}}} = \frac{\sum_{\forall node_j \in CH} E_{CH}^{res}(j)/|CH|}{\sum_{\forall node_j \in \widetilde{CH}} E_{\widetilde{CH}}^{res}(j)/|\widetilde{CH}|} \quad (6)$$

$$R_{location}^{CH} = \frac{\bar{D}_{\widetilde{CH}}}{\bar{D}_{CH}} = \frac{\sum_{\forall node_j \in \widetilde{CH}} d(node_i, BS)/|\widetilde{CH}|}{\sum_{\forall node_j \in CH} d(node_i, BS)/|CH|} \quad (7)$$

Practical WSNs employ battery-powered nodes, with residual energy indicated by the battery voltage. Nodes with higher energy and proximity to the BS exhibit a higher likelihood of becoming CHs. Given the NP-hard nature of this problem, an improved CS algorithm is proposed for the solution, as detailed in the subsequent section.

To mitigate excessive energy consumption among CHs, RNs are introduced to share the data transmission burden. RN selection depends on two primary criteria: superior energy levels relative to CNs and optimal spatial positioning between the CH and the BS to minimize energy-intensive transmissions. Unlike conventional approaches, our protocol assigns a dedicated RN to each CH, reducing communication overhead between these entities.

The RN selection process is guided by a fitness function (Eq. (8)) comprising two components: $R_{energy}^{EN}$ and $R_{location}^{RN}$. $R_{energy}^{EN}$, calculated in Eq. (9), represents the ratio of average RN energy to average CN energy, prioritizing energy-rich nodes for RN roles. $R_{location}^{RN}$, defined in Eq. (10), evaluates the relative position of a potential RN to its corresponding CH and the BS, aiming to minimize transmission distances.

$$F_{RN} = \beta \times R_{energy}^{RN} + (1 - \beta) \times R_{location}^{RN} \quad (8)$$

$$R_{energy}^{EN} = \frac{\bar{E}_{RN}}{\bar{E}_{CN}} = \frac{\sum_{\forall node_z \in RN} E_{RN}^{res}(z)/|RN|}{\sum_{\forall node_k \in CN} E_{CN}^{res}(k)/|CN|} \quad (9)$$

$$R_{location}^{RN} = \frac{\bar{L}_{CN}}{\bar{L}_{RN}} = \frac{\sum_{\forall node_k \in CN}\{d(node_k, BS) + d(node_k, CH_j)\}/|CN|}{\sum_{\forall node_z \in RN}\{d(RN_z, BS) + d(RN_z, CH_j)\}/|RN|} \quad (10)$$

By maximizing both $R_{energy}^{EN}$ and $R_{location}^{RN}$, the protocol ensures the selection of energy-efficient and strategically positioned RNs, thereby enhancing overall network performance. Similar to other protocols, CH and RN selection is centralized at the BS. SNs are given an identifier (ID) based on their location. The clustering process commences with nodes broadcasting residual energy and location information via *Node-MSG* messages. The BS selects CHs and disseminates their IDs through a broadcast message. Subsequently, CHs introduce themselves to the network using *CH-ADV* messages. A similar process is followed for RN selection and announcement (*RN-ADV* messages).

CNs determine their cluster membership by selecting the CH requiring the least transmission energy based on received *CH-ADV* messages. Upon cluster selection, nodes notify the CHs via *JOIN-REQ* messages. The CH functions as a control center, establishing a TDMA scheduler and disseminating it through *SCHEDULE-MSG* messages. This synchronization mechanism reduces energy usage and enhances spectral efficiency by enabling nodes to power down their radios during idle periods. The data transmission phase adheres to the TDMA schedule, with CNs sending data to their CHs. The CH collects data and relays it to the RN, which ultimately transmits aggregated data to the BS.

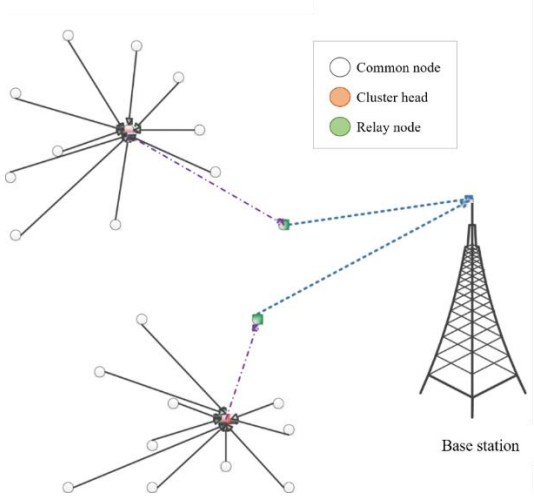


Fig. 2. Network architecture of the proposed protocol.

## V. Proposed Algorithm for Cluster Node Updating

The conventional CS algorithm mimics the intelligent behavior of crows to solve optimization problems [21]. It involves the following steps:

- Initialization: Define the optimization problem, set parameters, and initialize crow positions randomly within defined bounds.
- Memory update: Store the initial position of each crow.

$$Crows_{i,t} = \begin{bmatrix} x_i^1 & \cdots & x_i^d \\ \vdots & \ldots & \vdots \\ x_N^1 & \cdots & x_N^d \end{bmatrix} \quad (11)$$

$$CrowsMemory_{i,t} = \begin{bmatrix} m_i^1 & \cdots & m_i^d \\ \vdots & \ldots & \vdots \\ m_N^1 & \cdots & m_N^d \end{bmatrix} \quad (12)$$

- Position update: If crow *j* is unaware of crow *i*, update crow *i*'s position using Eq. (13) and a local or global search based on *fl*. If crow *j* is aware of crow *i*, update crow *i*'s position randomly.

$$x_{i,t+1} = x_{i,t} + r_i \times fl \times (m_{j,t} - x_{i,t}) \quad (13)$$

$$x_{i,t+1} = a\ random\ position \quad (14)$$

- Evaluation: Evaluate the fitness of new positions and update crow memories with better solutions.
- Termination: Steps 2-4 are repeated until generation limit is met.

The Modified Crow Search (MCS) Algorithm is an improvement over the conventional CS. It introduces two key modifications:

Dynamic awareness probability: Instead of a fixed *AP*, the MCS algorithm uses a parameter *K* that dynamically adjusts the probability of a crow being aware of another crow's following. This promotes exploration in early generations and exploitation in later generations.

$$K_t = round\left(K_{max} - \frac{K_{max} - K_{min}}{t_{max}} \times t\right) \quad (15)$$

Adaptive flight length: The MCS algorithm calculates the flight length (*fl*) based on the distance between crows ($D_{i,j}$). This allows for a more focused search in promising regions.

$$fl_{i,t} = \begin{cases} 2 & if\ D_{i,j} > D_{thr} \\ fl_{thr} & if\ D_{i,j} \le D_{thr} \end{cases} \quad (16)$$

The conventional CS algorithm employs a repetitive optimization process that hinges on exploration and exploitation, modulated by the parameter *AP*, typically set to 0.1. This configuration predominantly biases the algorithm towards exploitation, often at the expense of exploration across all generations. As a consequence, the CS algorithm is susceptible to local optima and exhibits strong dependence on the initial population. To mitigate these limitations, this paper introduces a novel approach that incorporates a dynamically adjusted *AP*, correlated with the generation count, and employs two innovative equations to enhance exploration and exploitation.

$$AP = AP_{max} + \frac{AP_{max} - AP_{min}}{t_{max}} \times t \quad (17)$$

Similar to the standard CS, step 1 of A-CSA involves problem definition and parameter initialization. However, A-CSA introduces additional parameters: $AP_{max}$, $AP_{min}$, and *FAR* (Flight Awareness Ratio). $AP_{max}$ and $AP_{min}$ are pivotal for the dynamic *AP* mechanism.

Consistent with the conventional CS, A-CSA employs Eq. (11) and Eq. (12) to determine crew group size and initialize crow positions. Subsequently, the objective function evaluates the fitness of these initial positions.

A-CSA diverges significantly from the conventional CS in three key aspects. Firstly, A-CSA incorporates a dynamic *AP* that fluctuates with the generation count, as governed by Eq. (18). $AP_{max}$ and $AP_{min}$, bounded between 0 and 1, control the exploration-exploitation balance. A larger *AP* promotes exploration, while a smaller *AP* favors exploitation. Optimal algorithm performance necessitates a judicious selection of *AP*.

$$AP_t = AP_{min} + \frac{AP_{max} - AP_{min}}{ln(t)+1} \quad (18)$$

Secondly, in contrast to the random selection of a crow to follow in the conventional CS (Eq. (13)), A-CSA employs a FAR-based mechanism to guide crow *i* towards the best crow *j* ($gb_{j,t}$) as defined by Eq. (19). $r_{i,t}^2$ and $r_{i,t}^3$ are random values within the [0, 1] interval, and *FAR* is a predefined constant between 0 and 1. This modification enhances exploitation compared to the standard CS. A *FAR* approaching 0 prioritizes memory-based best solutions, while a value closer to 1 resembles the random selection of the conventional CS. By tuning *FAR* appropriately, the algorithm can achieve a harmonious balance between exploration and exploitation, thereby improving convergence.

$$x_{i,t+1} = \begin{cases} x_{i,t} + r_{i,t}^2 \times fl \times \left(m_{j,t} - x_{j,t}\right) & if\ r_{i,t}^3 \le FAR \\ x_{i,t} + r_{i,t}^2 \times fl \times \left(gb_{j,t} - x_{j,t}\right) & else \end{cases} \quad (19)$$

Thirdly, A-CSA refines the exploration phase of the conventional CS. While the latter employs a random search within the lb and ub bounds when the random number exceeds *AP*, A-CSA introduces a localized search mechanism through Eq. (20) as the generation progresses. This strategy mitigates the diminishing returns of global search in later generations. $r_{i,t}^4$ and $r_{i,t}^5$ are random values within the [0, 1] range.

$$x_{i,t+1} = \begin{cases} 2x_{i,t} + \left(lb + r_{i,t}^5 \times (lb - ub)\right)/t & if\ r_{i,t}^4 \le 0.5 \\ a\ random\ position & else \end{cases} \quad (20)$$

The optimization process iteratively executes Steps 2-4 until the generation count reaches the predefined maximum ($t_{max}$), yielding the final solution. Algorithm 1 presents the pseudocode of A-CSA.

**Algorithm 1** Pseudocode of A-CSA

**Input:**
Initialize control parameters: $AP_{max}, AP_{min}, FAR, fl, N, pd, t_{max}$
Randomly generate and store the initial positions of all crows in the solution space
Evaluate the initial fitness of each crow
**Begin iteration:**
Repeat until the maximum number of iterations $t_{max}$ is reached:
Randomly select the crow positions to update
**For** each crow $i = 1$ *to* $N$:
  Compute the dynamic awareness probability $AP_t$
  Generate a random number $r^1 \in [0,1]$
  **If** $r^1 \geq AP_t$:
    Generate another random number $r^3 \in [0,1]$
    **If** $r^3 < FAR$:
      Update position using Equation 19a
    **Else**
      Update position using Equation 19b
  **Else**
    Generate another random number $r^4 \in [0,1]$
    **If** $r^4 \leq 0.5$:
      Update position using Equation 20
    **Else**
      Assign $x_{i,t+1}$ a random position within the bounds
**End for**
Evaluate the updated positions and compute fitness values
Update memory based on improved solutions
**End repeat**
Report the best-found solution and convergence results

The computational complexity of the proposed A-CSA algorithm primarily stems from the repeated evaluation of the fitness functions for CH and RN selection and the iterative update of crow positions. Let $N$ represent the number of nodes, $G$ the number of generations, and $C$ the number of candidate crows. The per-generation complexity is $O(C{\cdot}N)$, resulting in an overall complexity of $O(G{\cdot}C{\cdot}N)$. As clustering and optimization are carried out at the base station, which is not resource-constrained, this overhead remains acceptable for practical deployments. Future enhancements may involve parallel implementations to reduce computation time further.

## VI. Results and Discussion

This section presents a comprehensive investigation of the suggested method's effectiveness through simulation analyses. The protocol's efficacy in constructing energy-efficient routing hierarchies for WSNs is assessed, with a particular focus on applications demanding long network longevity and effective data aggregation, e.g., monitoring environments.

Key parameters, including network lifetime, node count, BS positioning, and network dimension, were considered in the comparative analysis of various routing protocols. MATLAB was employed for simulation modeling and programming, with average values derived from 20 simulation runs to enhance result reliability. Simulation variables are summarized in Table III.

Fig. 3 illustrates the convergence rate of the objective function's fitness value, demonstrating convergence within 50 iterations. Consequently, the algorithm's maximum iteration count was set to 50.

A comparative analysis with a CS-based protocol is presented in Fig. 4. Network lifetime metrics employed include FND, Last Node Dead (LND), and Half Number of Nodes Dead (HND). A-CSA significantly improved over the CS-based approach, with FND, HND, and LND extended by 98%, 101%, and 105%, respectively.

TABLE III Simulation Variables

| Feature | Variable | Value |
|---|---|---|
| Radio model | $E_{DA}$ | *5nJ/bit/signal* |
| | $d_0$ | *75m* |
| | $E_{mp}$ | *0.0013pJ/bit/m$^4$* |
| | $E_{fs}$ | *10pJ/bit/m$^2$* |
| | $E_{elec}$ | *50nJ/bit* |
| Network | Initial energy of nodes | *2J* |
| | BS location | *(50,175)* |
| | Dimension | (0,0)~(100,100) |

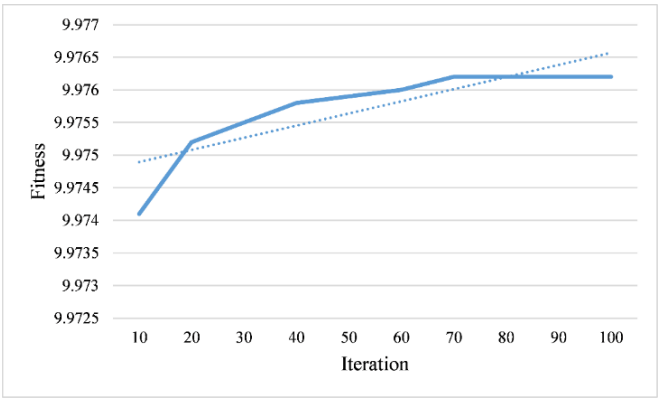


Fig. 3. Convergence rate.

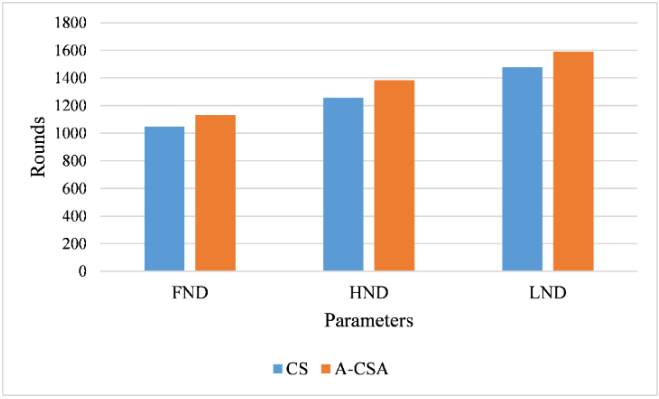


Fig. 4. Comparative analysis of network lifetime metrics.

To measure the lifetime efficiency of the suggested protocol, three distinct situations were considered varying in terms of node count, BS position, and network area size, as detailed in Table IV. The proposed protocol was benchmarked against SEECH, TCAC, and LEACH. Fig. 5, Fig. 6, and Fig. 7 visualize the count of alive nodes over time. A-CSA consistently outperformed the other three compared protocols.

TABLE IV EVALUATION SCENARIOS

| Parameter | 1st situation | 2nd situation | 3rd situation |
|---|---|---|---|
| Node count | 100 | 500 | 1000 |
| BS position | (50,175) | (50,200) | (100,300) |
| Dimension | (100,100) | (100,100) | (200,200) |

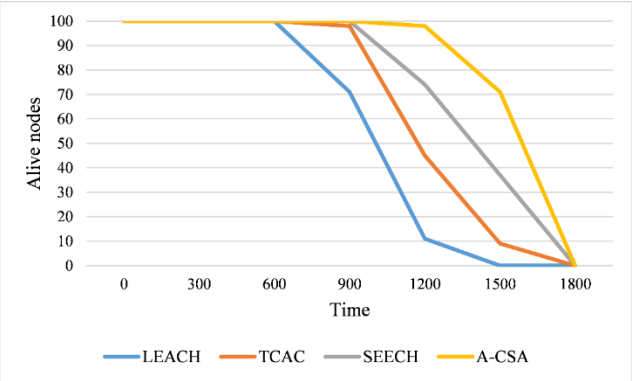


Fig. 5. Network lifetime comparison for first scenario.

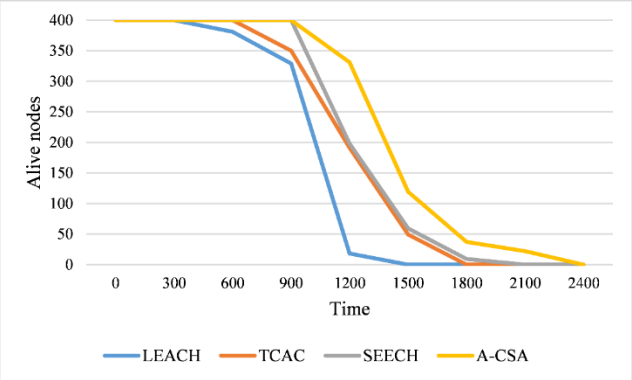


Fig. 6. Network lifetime comparison for second scenario.

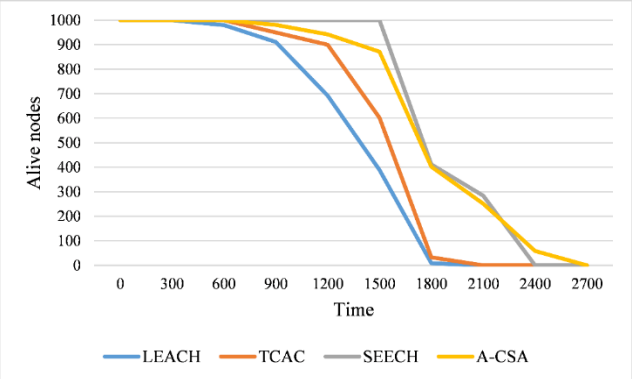


Fig. 7. Network lifetime comparison for third scenario.

Unlike existing models that rely on static or heuristic-based decisions, A-CSA dynamically adapts its search behavior over generations, resulting in better convergence and more energy-efficient clustering. Moreover, the integration of a bi-objective fitness function for both CH and RN selection provides an edge in maintaining balanced energy distribution, especially in dense and large-scale networks. These improvements position A-CSA as a competitive and scalable alternative to traditional and hybrid clustering approaches.

## VII. CONCLUSION

Energy efficiency is a paramount challenge in WSNs. Clustering and routing strategies are commonly employed to address this issue. However, these problems are classified as NP-hard optimization problems, necessitating heuristic approaches. Swarm intelligence algorithms have emerged as promising candidates for obtaining near-optimal solutions to these complex challenges. This paper introduced a novel clustering protocol for WSNs that leverages RNs to alleviate the energy burden on CHs. An enhanced CS algorithm is proposed to optimize cluster formation, minimizing transmission distances and energy consumption. This approach effectively prolongs the network lifetime. Comprehensive simulations under diverse network conditions, including varying node densities, network areas, and BS positions, demonstrated the protocol's superior energy efficiency compared to existing clustering protocols. By balancing energy consumption among nodes and reducing overall energy expenditure, the proposed protocol significantly extends the network lifetime.

While the primary focus of this study was on energy efficiency and network longevity, critical factors in battery-constrained WSNs, we acknowledge that comprehensive validation should also consider metrics such as delay, throughput, and packet delivery ratio . Although our simulation results include node activity trends that indirectly reflect throughput, detailed quantitative evaluations of delay and PDR were not included in this version. Future work will incorporate these metrics to provide a more holistic assessment of the protocol's suitability for time-sensitive and high-reliability IoT applications. Additionally, to enhance the applicability of A-CSA in dynamic IoT environments, we aim to incorporate mobility models and traffic-aware mechanisms, enabling the protocol to adapt to node mobility, varying network topologies, and fluctuating traffic loads commonly encountered in real-world deployments.

## FUNDING

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# Understanding Brain Network Stimulation for Emotion Analyzing Connectivity Feature Map from Electroencephalography

Mahfuza Akter Maria[1], M. A. H. Akhand[2], Md Abdus Samad Kamal[3]
Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna-9203, Bangladesh[1, 2]
Graduate School of Science and Technology, Gunma University, Kiryu 376-8515, Japan[3]

***Abstract*—In understanding brain functioning by Electroencephalography (EEG), it is essential to be able to not only identify more active brain areas but also understand connectivity among different areas. The functional and efficient connectivity networks of the brain have been examined in this study by constructing a connectivity feature map (CFM) with four widely used connectivity methods from the Database for Emotion Analysis Using Physiological Signals (DEAP) emotional EEG data to research how this connectivity's patterns are influenced by emotion. According to the investigation results, emotions are mainly related to the parietal, central, and frontal regions. The parietal region is more responsible for emotion alteration among these three regions. Positive emotions are associated with more direct correlations and dependencies than negative ones. When experiencing negative emotions, the regions of the brain function more synchronously as well as there are less flow of information. Whether direct or inverse, there is less correlation between brain regions in the higher frequency band than in the lower frequency band. Higher frequencies are associated with increased dependence and directed information transfer between brain regions. Generally, the electrodes in the same lobe show stronger connectivity than those in different lobes. At a glance, the present study is a comprehensive analysis to understand brain network stimulation for emotion from EEG, and it significantly differs from the existing emotion recognition studies typically focused on recognition proficiency.**

***Keywords*—Brain connectivity; connectivity feature map; electroencephalography; emotion**

## I. Introduction

Interaction between brain areas have been recognized as a critical ingredient needed to understand brain function. Neuroimaging techniques are valuable for studying how the brain processes human emotions and activities. Emotion research has received increased attention from cognitive scientists and neurobiologists in recent decades, owing to its importance in decision-making, well-being, mood, personality, and psychotic diseases [1]. Electroencephalography (EEG) is a neuroimaging method that uses its sensors in the brain to record the electrical impulses generated by neural activity (i.e., electrodes or channels) affixed to the brain; it captures the changes in voltage brought on by ionic current flows in the neurons of the brain [2], [3], [4]. Recently, EEG has become popular for studying the brain's responses to emotional stimuli for its superior temporal resolution, noninvasiveness, portability, ease of use, and reasonably affordable speed [4], [5]. EEG is a composite signal that is composed of sub-bands such as Alpha (8–12 Hz), Beta (13–29 Hz), and Gamma (30–50 Hz) [6]. These sub-bands may provide a more accurate representation of the constituent neural process activity [7]. Connectivity features from the EEG signal can provide valuable information regarding brain connectivity behind emotion as these features analyze the interaction between different brain areas.

Several methods can measure the connectivity among EEG signals from different brain regions. Examples of such methods include Pearson correlation coefficient (PCC) [8], cross-correlation (XCOR) [9], phase locking value (PLV) [10], mutual information (MI) [11], normalized MI (NMI) [12], partial mutual information (PMI) [13], and transfer entropy (TE) [14]. PCC and XCOR are linear functional connectivity methods which can only detect linear dependencies between two signals or variables; PLV is nonlinear functional connectivity that represents the phase synchronization between two signals or variables. MI is nonlinear functional connectivity method, which measures the amount of shared information, whereas TE stands for effective nonlinear connectivity, which measures the directional flow of information between two brain regions. MI and TE are information-theoretic measures based on Shannon entropy [15]. Both NMI and PMI are two variants of MI. Such methods can be applied to signals collected through EEG electrodes to extract the connectivity features of the signals. The extracted features can be mapped into a two-dimensional matrix called a connectivity feature map (CFM). Emotion recognition (ER) and investigating brain mechanisms from CFM have become popular recently in the field of emotion research [16]–[22].

This study aims to analyze and understand brain network connectivity stimulation for different emotions through CFM from EEG, overcoming the limitations of the existing studies. The existing studies mainly focused on ER, and a few studies considered to investigate the brain mechanism behind/along ER. This study considers diverse connectivity methods for CFM construction and analysis to understand brain network stimulation emotion. Four frequently used connectivity methods, PCC, PLV, MI, and TE, were chosen. This study investigates connectivity represented in three sub-frequency bands named Alpha, Beta, and Gamma. Extensive studies using the developed CFMs have been conducted on the DEAP

benchmark EEG dataset. An overview of the primary contributions of this work is provided below:

*1)* Brain network stimulation outcomes have been reviewed from existing studies.

*2)* Using four diverse, widely used connectivity methods, PCC, PLV, MI, and TE, CFMs are constructed for the DEAP dataset.

*3)* Distinctive and rigorous analysis of CFMs has been conducted to unveil discerning remarks on brain network connectivity levels (weak/strong) concerning stimulation for emotions with the frequency bands and brain lobes.

*4)* This study's findings are contrasted with those of comparable state-of-the-art research and identified novelty of the study.

The rest of this study is structured as follows. Section II briefly reviews prominent ER studies emphasizing brain network connectivity stimulation. The methodology to investigate brain mechanisms from CFM is described in Section III. Section IV presents the findings by analyzing CFM using the DEAP dataset. Section V presents a comparative discussion of the findings of the present study with related existing studies. At last, Section VI concludes the paper with a few remarks.

## II. Literature Review

Emotion is the basic characteristic of human beings, and the brain is the root of emotion exposure. Emotion recognition (ER) analyzing EEG signals is well-studied in a number of existing studies. Proficiency of ER from EEG is the common main goal of those studies; however, several studies slightly focused on understanding brain network connectivity stimulation for different emotions and emotional states through CFM from EEG. The existing studies may be categorized under findings with respect to (w.r.t.) emotional states, brain regions, and frequency bands. The ensuing subsections provide a concise overview of notable ER research categorically.

### *A. Investigation Concerning Frequency Bands*

The effect of different frequency bands on brain connectivity was investigated in a few studies [23], [24]. Li et al. [23], extracted the PLV feature and fused it with several other individual channel features; the fused feature was then classified by stacking an ensemble learning framework for ER. Brain function was also investigated with PLV feature under Theta, Alpha, Beta, and Gamma sub-frequency bands, from where it was identified that the PLV of the lower frequency bands (i.e., Theta and Alpha) is greater than those of higher frequency bands (i.e., Beta and Gamma). The same sub-frequency bands and PLV feature were also used by Cui et al. [24], to classify emotion and to analyze brain connectivity; they drew some conclusions that the Beta band has the lowest PLV, whereas the Theta band's PLV is significantly higher than other bands'.

### *B. Investigation Concerning Emotional States*

Brain mechanisms concerning different emotions, such as positive and negative, have been investigated in several studies [12], [20], [21], [22], [17], [25]. Wang et al. [12], used NMI as a connectivity method to construct CFM. The aim of the study [12] was channel selection, where emotion classification was done with a support vector machine (SVM); the study also drew some conclusions on brain function behind emotion from where it was identified that the high Arousal low Valence state was found to have a wider active brain areas. Khosrowabadi et al. [20], used MI and another functional connectivity feature named magnitude MI and squared coherence estimate (MMSCE) to recognize emotion with SVM and K-nearest neighbor (KNN) classifier; they identified that various emotional states are accompanied by various types of functional brain connectivity. Liu et al. [21], performed emotion classification with the Xception network where brain mechanism also investigated with connectivity feature named coherence; the study found that the functional network made by low Valence-Arousal emotion revealed more active (i.e., higher coherence) functional connectivity than the one made by high Valence-Arousal emotion. When using the phase slope index (PSI) approach to study brain connectivity, Costa et al. [22], discovered a phenomenon whereby multi-channel EEG signals for sad emotions are more synchronized than those for happy emotions. Wang et al. [17], classified emotion with the PLV feature by Graph CNN; the PLV feature was also used to investigate brain connectivity. According to the study [17], the phase-locking value in the pleasant condition is lower than in the sad condition, which indicates that the pleasant mood is less active in the brain area. Recently, Wang et al. [25], identified from PLV feature that PLV values in positive emotions are generally smaller than in negative emotions; they also analyzed CFM concerning time periods and identified that there are little differences in connection patterns for the same emotions in different time periods.

### *C. Investigation Concerning Different Brain Regions*

Several studies investigated responses of specific brain regions on different mental states by analyzing the CFMs with individual connectivity methods. Gao et al. [5], employed two effective connectivity features named TE and Granger causality (GC) for classifying stress and calm state with three classifiers (i.e., SVM, random forest, and decision tree); they highlighted from the GC that the parietal and frontal lobes show stronger connectivity during the stress state; and they also discovered from TE that there was a greater information exchange between the C4 and Fp1 channels under pressure. Chen et al. [8], used PCC, PLV, and TE feature methods to recognize emotion with domain adaptive residual convolutional neural network (CNN) as a classifier. Along with ER using the three feature methods, they investigated brain mechanisms through PCC and PLV features; it was found from CFM constructed with PCC that the brain’s emotional activity is more perceptible in the occipital and parietal regions, and the CFM with PLV revealed that the phase consistency is relatively strong in the occipital, frontal and parietal regions, while the phase consistency is poor in other regions. For emotion recognition, Kong et al. [16], used sparse representation-based classification with connectivity feature PSI; the PSI method was also used for brain connectivity analysis from where it was found that, in sad emotion, the right prefrontal cortex (PFC) has stronger nodal connections than the left PFC, whereas, in happy emotion, the left PFC's nodal connection strength is stronger than the right PFC's. Graph CNN was used with the PLV feature by Wang et al. [15], to classify emotion under five sub-frequency bands (i.e., Delta, Theta, Alpha, Beta, and Gamma), but a single frequency band was used

to investigate brain network and drew conclusions that emotions are related to mainly the temporal lobe. The study also showed that, during positive and negative emotions, the left and right forebrain generates strong EEG activity, respectively; the study shows that emotions are greatly correlated with the forebrain. Zhu et al. [18], used CNN to classify emotion with the phase lag index (PLI) feature and also explored phase synchronization of brain signals with that feature and found that, generally, the connectivity between the channels of the right frontal region was stronger than those of the left frontal region.

## III. Methodology

In this study, connectivity is measured using different popular methods on the benchmark EEG dataset to understand brain network connectivity stimulation for emotion. Fig. 1 illustrates the framework of the proposed study; the EEG data preprocessing, CFMs construction using different connectivity methods, and analysis of the CFMs are the major steps of the study. The following subsections describe the EEG dataset and the connectivity methods to construct CFM.

### *A. Dataset Selection and Data Preprocessing*

This study utilizes one of the most popular and well-studied EEG datasets for emotion detection, the Database for Emotion Analysis Using Physiological Signals (DEAP) [26]. In DEAP dataset development, 40 emotive music videos were utilized as stimuli on 32 individuals (i.e., subjects), and EEG and other peripheral physiological signals of individual subjects were collected as responses against individual videos. The database also includes subjective scores that describe the levels of Valence, Arousal, Liking, and Dominance of the emotional states produced by watching the videos. The preprocessed EEG signals from the database are used in this study, where the signal frequency range is 4.0 to 45.0 Hz. Of the 40 channels, 32 are used for EEG signals, and the remaining channels are used for peripheral physiological inputs. The ordering of the electrodes in the preprocessed version of the database is as follows: Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4, O2.

In the DEAP dataset, an EEG signal is 63 seconds long, and the first 3 seconds of data are the pre-trial baseline. By removing 3 seconds of pre-trial data, the remaining 60 seconds of data are processed for this study. For this investigation, a sliding time window of 8-second with a 4-second overlap is used to segment EEG data. Thus, there are 14 segments totaling 60 seconds. The total number of segments for each participant is 14 × 40 (video) × 32 (channel). EEGLAB [27] is used to filter the signal to extract Alpha, Beta, and Gamma sub-bands.

Among the four quality levels available in the DEAP dataset, Valence and Arousal are chosen in this study as they are well-studied scales for classifying emotions. In the dataset, the ratings for Valence and Arousal range from 1 (low) to 9 (high). Similar to the work in [28], Valence and Arousal are considered as high Valence (HV) and high Arousal (HA) for values above 4.5 and low Valence (LV) and low Arousal (LA) for less than or equal to 4.5. At a glance, HV indicates positive emotion, LV indicates negative emotion, HA indicates active emotion, and LA indicates passive emotion [29]. The positive and negative emotions or active and passive emotions can be represented in 2D space according to Russell's model [29], as shown in Fig. 2.

### *B. Connectivity Feature Map (CFM) Construction*

Feature extraction has recently emerged in new dimensions through CFM construction using different connectivity measures [6]. This work takes into account several connectivity measures (linear, nonlinear, directed, etc.) for feature extraction as well as CFM creation. In a single experiment, the level of connectivity between two electrodes indicates the interaction between two brain areas. Depending on emotional or cognitive activities, this interaction could be a direct correlation, an inverse correlation, or synchronization. Four popular candidate connectivity methods were chosen from linear functional, nonlinear functional connectivity and nonlinear effective connectivity categories. The selected methods are PCC, PLV, MI, and TE.

The linear correlation between two signals, X and Y, is measured by PCC and is calculated as

$$PCC_{XY} = \frac{n\sum X_i Y_i - \sum X_i \sum Y_i}{\sqrt{n\sum X_i^2 - (\sum X_i)^2}\sqrt{n\sum Y_i^2 - (\sum Y_i)^2}}, \quad (1)$$

where, n denotes sample size, and $X_i$ or $Y_i$ is the individual sample points indexed with i. PCC's value varies from -1 to 1. (-1): complete linear inverse correlation, (0): no linear interdependence, (1): complete linear direct correlation between the two signals.

PLV defines the phase synchronization between two signals, which is measured by the rules as follows-

$$PLV(X,Y) = \frac{1}{T}\left|\sum_{t=1}^{T} exp\{j(\varphi_X^t - \varphi_Y^t)\}\right|, \quad (2)$$

where, $\varphi^t$ denotes the phase of the signal at time t, X, and Y are two electrodes, and T is the length (time) of the signal. PLV has a value between 0 and 1, denoting perfect independence and perfect synchronization, respectively.

MI is an information theoretic approach to measuring shared information between two variables. The following is the definition of MI between two random variables, X and Y:

$$MI(X,Y) = H(X) + H(Y) - H(X,Y), \quad (3)$$

where, H denotes Shannon entropy [15]. Entropy is measured by calculating the probability using the fixed bin histogram approach. There are 10 bins utilized in the computation. The marginal entropies of the two variables X and Y are H(X) and H(Y), respectively, and their combined Entropy is H(X, Y). The range of MI's value is: $0 \leq MI(X,Y) < \infty$. If MI(X, Y) is equal to 0, then X and Y are independent. If MI(X, Y) is greater than 0, then X and Y are dependent.

The directed information flow from a signal or time series Y to another signal X is measured by TE.

$$TE_{Y\to X} = H(X_t, Y_t) - H(X_{t+h}, X_t, Y_t) + H(X_{t+h}, Y_t) - H(X_t) \quad (4)$$

If the future of X, i.e., $X_{t+h}$ is denoted by w, then transfer Entropy $TE_{Y\to X}$ can be computed as:

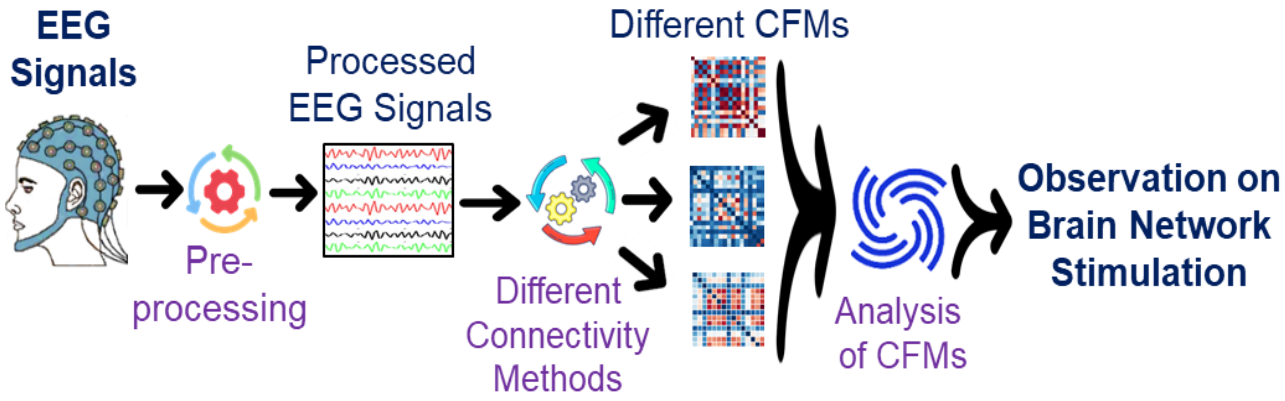



Fig. 1. The framework of the proposed study to observe brain network stimulation from EEG for emotion.

$$TE(w,X,Y) = H(w,X,) + H(X,Y) - H(X) - H(w,X,Y) \quad (5)$$

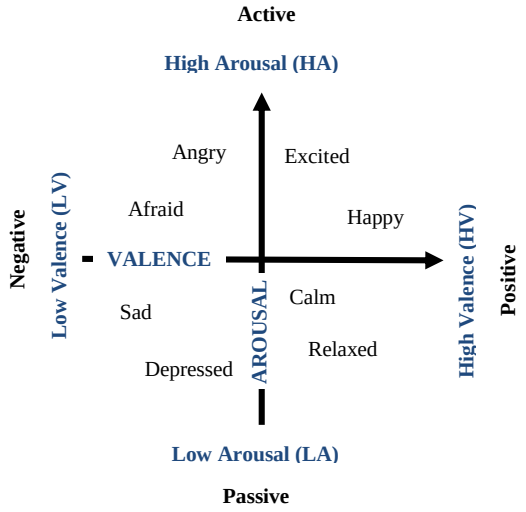



Fig. 2. Russell's emotion model.

The ranges of TE value are $0 \leq TE_{Y \to X} < \infty$. If the TE = 0, then there is no directed flow of information, i.e., no causal relationship between the signals. TE > 0 means that there is a causal relationship between them.

When it comes to CFM, these variables are signals from particular EEG channels. Connectivity features are extracted for each pair $(X, Y)$ of EEG electrodes. The connectivity features extracted from all electrode pairs can be mapped into a matrix (i.e., CFM). The matrix element at $(X, Y)$ describes the connectivity strength between the signals collected from the Xth and Yth electrodes. As the data are segmented in the preprocessing stage, a total of 17,920 CFMs are constructed under each frequency band for each connectivity method from all 32 participants, each with 40 trials.

## IV. Results of CFM Analysis on Brain Network Stimulation for Emotion

CFM analysis for brain networks is the main contribution of this study to observe the connectivity depiction of emotion. The following subsections briefly describe brain network stimulation for emotion-analyzing CFM in different dimensions/directions. CFMs representation as heat maps is commonly available in the existing studies [6] that are followed in this study.

### *A. Effect of Sub-Bands on Emotion Analysis*

The CFM created from the three frequency bands (i.e., Alpha, Beta, and Gamma) with the four connectivity methods (i.e., PCC, PLV, MI, and TE) under positive and negative emotions are displayed in Fig. 3. The response of the brain of a person to an emotion may be different from another person. Therefore, the constructed CFMs are presented for two individual participants (participant 1 and participant 32) as well as the average CFM of the total 32 participants.

It can be observed for PCC in Fig. 3(a) that, for participant 1, red and blue colors are lighter in the Gamma band, and the colors are darker in the Alpha band. The Beta band CFM colors remain in the middle of the two. In the case of Participant 2, the CFMs in the Beta band contain the lowest PCC value than that of the Alpha and Gamma bands. When the average CFM is considered, it can be observed that the correlation between brain regions, either a direct correlation or inverse correlation, is higher in the lower frequency band than in the higher frequency band, which is similar to Participant 1. As shown in Fig. 3(b), CFMs for both participants and the average CFMs, the Gamma band has a considerably larger PLV than the other bands, while the Beta band has the lowest. This implies that the Gamma frequency band had higher synchrony. In the case of MI in Fig. 3(c), the Beta band holds the highest MI value for Participant 1, and the Gamma band holds the highest MI value for Participant 32. When the CFMs from all participants are averaged, it is found that the mutual dependency between brain regions increases with higher frequency. Fig. 3(d) shows the CFMs constructed with TE, where it can be seen that with increased frequency, information flows more often between different parts of the brain.

Among the three frequency bands, the positive and the negative CFMs are more easily distinguishable in the Gamma frequency band. A number of studies have also identified that the Gamma band exhibits better emotional observation than the Alpha and Beta bands [19], [30]. So, further discussions in the next sections are presented with the average CFMs from the Gamma band only for concise observation.

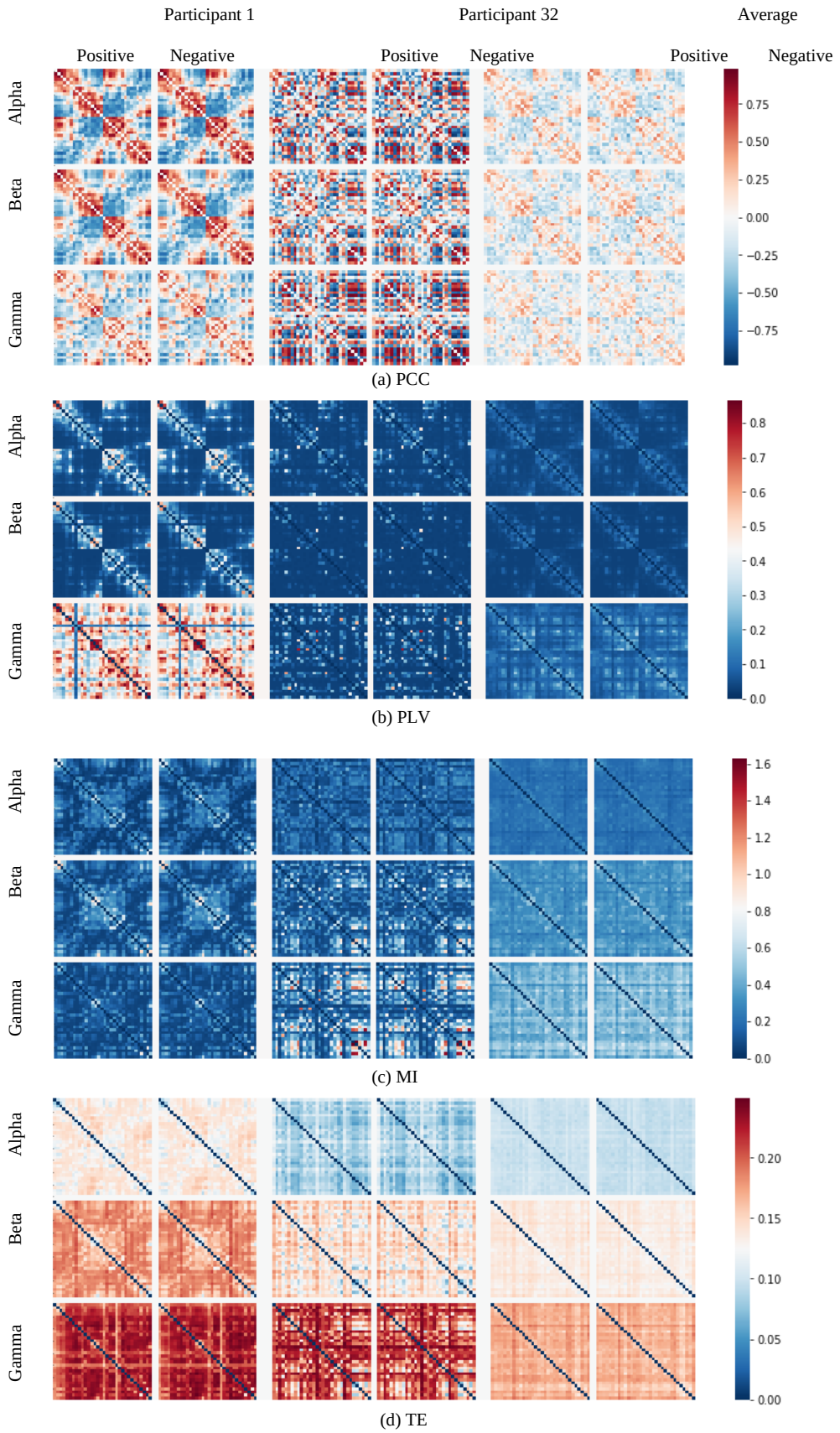



Fig. 3. CFM with different connectivity methods in alpha, beta, and gamma frequency bands for the positive and negative emotion.

### B. Connectivity Strength in Positive and Negative Emotions

Connectivity methods offer useful information about brain connectivity behind emotions. As discussed in the previous section, high Valence emotions are regarded as positive emotions and low Valence emotions are regarded as negative emotions. Fig. 4 illustrates how changes in emotions affect two brain regions' correlation, phase synchronization, mutual dependence, as well as causal relationship. The linear correlation between two brain areas is measured by PCC. The PCC-constructed CFM for positive and negative emotions in the gamma band is displayed in Fig. 4(a). Negative PCC values (blue pixels of the figure) denote an inverse linear correlation between two areas of the brain, and positive PCC values (red pixels of the figure) denote a direct linear correlation. As can be shown from Fig. 4(a), there are more locations with a strongly inverse correlation for negative emotion than for positive emotion. As compared to the CFM of positive emotion, the blue pixels in Fig. 4(a) are darker when representing negative emotion. For better visualization, a few areas are marked with blue rectangles. It implies that during unpleasant emotions, there is a greater inverse correlation between brain regions. Positive CFM shows darker red pixels than negative CFM, indicating a more direct linear correlation between brain regions during positive emotion than during negative emotion. Such few areas are marked with red rectangles.

Phase synchronization between two brain areas is described by PLV. Two signals are totally independent when the PLV value is 0; synchronization between the signals is indicated when the PLV value is greater than 0, and perfect synchronization is indicated when the PLV value is equal to 1. The CFM built for both positive and negative emotions utilizing PLV in the gamma frequency range is displayed in Fig. 4(b). In the CFM, a large phase-locking value is represented by red pixels, and a lesser phase-locking value is represented by blue pixels. Positive emotions have a phase-locking value that is comparatively lower than negative emotions, as seen in Fig. 4(b). Such few areas are marked with red rectangles. Therefore, in the negative state, the phase synchronization of distinct brain areas is greater. The higher values show that the synergy between various brain regions is increased during negative emotions, which results in synchronous oscillations. It is thus considered that the human brain pays greater attention to details in negative emotions than in happy emotions.

Fig. 4(c) and Fig. 4(d) displays the CFMs created for positive and negative emotions employing MI and TE, respectively. The MI calculates how dependent the two areas of the brain are. The more dependent two brain regions are on one another, the higher the value of MI. Fig. 4(c) shows that when an individual experiences negative emotions, there is an increase in the dependency between different brain regions and this phenomenon can be easily observed through the red-marked area. TE quantifies the directed transfer of information across different regions of the brain. More information transfer between two different parts of the brain results in a higher score for TE. It is evident from Fig. 4(d) that the negative CFM pixels are lighter than the positive CFM pixels, which can be easily seen through the white rectangular area, suggesting that positive emotions have a greater directed information flow than negative emotions.

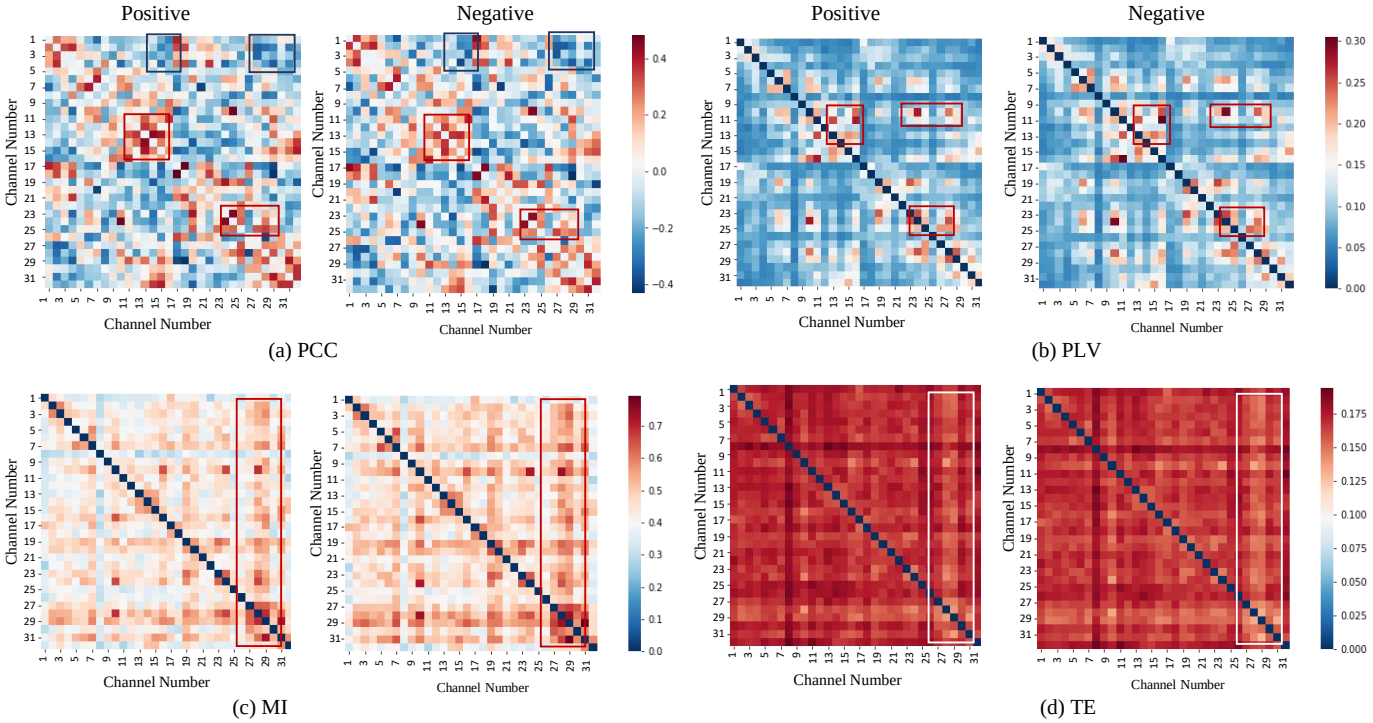



Fig. 4. CFM with different connectivity methods in Gamma band for the Positive (high Valence) and Negative (low Valence) emotions.

### C. Brain Region Distinctiveness on Emotion

Observing the effects of stimulation in brain regions on emotional consequences by analyzing the CFMs with individual connectivity methods is interesting. Fig. 5 illustrates higher and lower brain connectivity regions based on the analysis performed in the previous section with Fig. 4. From the PCC connectivity matrix in Fig. 4(a), it is seen that signals from nearly placed electrodes are highly correlated both in positive and negative emotions. For example, electrodes 17 and 18 (i.e., Fp2, AF4), electrodes 13 and 14 (i.e., PO3 and O1), electrodes 23 and 24 (i.e., FC2 and Cz), and electrodes 10 and 24 (i.e., CP1 and Cz) are placed nearly in the scalp and the PCC value for each pair of the electrode are high. Similarly, from the PCC matrix, it is also observed that inversely correlated electrodes are located far away (e.g., AF4 and P4). The highly correlated electrodes are marked in Fig. 5(a), where red lines indicate higher direct correlations and the blue line indicates higher inverse correlation.

Fig. 4(b) (for PLV) shows that the degree of some electrodes is noticeably higher than that of other electrodes. This means that some brain regions with higher degree electrodes may be in charge of producing specific emotions since they are more involved and synchronized with other brain regions. After summing all the PLV values for individual electrodes, it is found that both Positive and Negative CFM in Fig. 4(b), electrode 16 (i.e., Pz) holds the highest PLV value in the matrix, and the second highest value contains electrode 10 (i.e., CP1). Visual inspection of the figure also proves this. The third highest value contains electrodes 28 and 11 (i.e., CP2 and P3) in Positive and Negative CFM, respectively. The fourth highest value contains electrodes 11 and 28 (i.e., P3 and CP2) in Positive and Negative CFM, respectively. As mentioned, all the electrodes are in the parietal lobe; from here, it can be concluded that emotions are mainly related to the parietal lobe. The overall less synchronization can be seen with the electrodes 1, 8, 12, 13, 17, 18, 21, 26, and 30 (i.e., Fp1, T7, O1, P7, Fp2, AF4, F8, T8, and P8), which are located far from the electrode Cz or the center of the scalp. The distinction between positive and negative emotion can be easily seen through electrodes 10, 11, 16, and 27 (i.e., CP1, P3, Pz, and CP6), which means the parietal lobe is more sensitive to emotion alteration. The electrodes having higher and lower PLV values are marked in Fig. 5(b), where red highlights indicate higher PLV value and blue highlights indicate lower PLV value.

Similarly, from the MI connectivity matrix in Fig. 4(c), it can be observed that electrodes in parietal, central, and frontal regions such as C3, CP1, Pz, Fz, CP2, P4, and PO4 (i.e., 7, 10, 16, 19, 28, 29 and 31) hold higher MI values. The electrodes are marked in Fig. 5(c). The color variances between positive and negative CFM can also be easily seen through these electrodes, which indicates these brain regions are more sensitive to emotion alteration. Most of the electrodes, as mentioned above, are from the parietal lobe, i.e., among these three regions, the parietal region is more responsible for altering emotion.

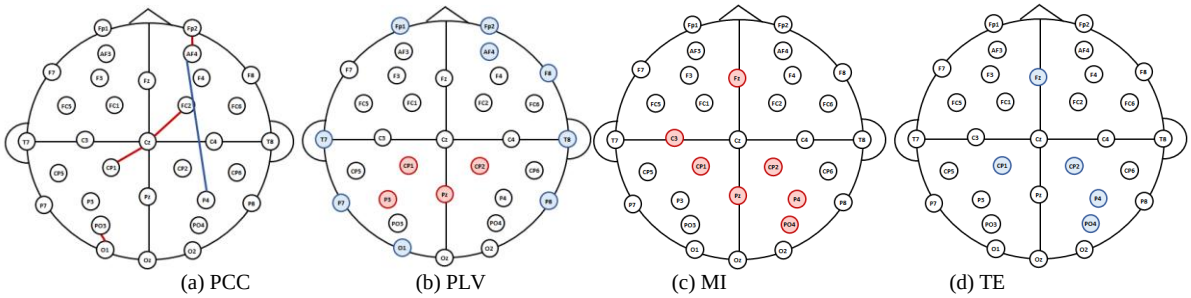
Section III(B) discusses that variation in CFM values of positive and negative emotion are opposite for MI and TE; positive CFM contains lower MI values and higher TE values. This phenomenon can be easily observed through the parietal, central, and frontal region's electrodes CP2, P4, Fz, PO4, and CP1 (i.e., electrodes 28, 29, 19, 31, and 10) in Fig. 4(d), which contain lower TE values. The electrodes are also marked in Fig. 5(d).

The findings from the CFM of the Gamma band discussed in Sections III(B) and III(C) are also satisfied by the Alpha and Beta band's CFM in Fig. 3, although the Gamma band's CFMs are easily observable. From all the CFM, it is also identified that, in general, the electrodes located in the same lobe show stronger connectivity than the electrodes located in different lobes.

### D. Connectivity Strength in Active and Passive Emotions

As discussed in the previous section, high Arousal (HA) emotions are regarded as active emotions and low Arousal (LA) emotions are regarded as passive emotions. Fig. 6 shows how correlation [Fig. 6(a)], phase synchronization [Fig. 6(b)], mutual dependency [Fig. 6(c)], and causal relationship [Fig. 6(d)] between two brain regions change with the changes in intensity (levels of Arousal) of emotions. These are the average CFMs created from the Gamma frequency band under active and passive emotions. From Fig. 6(a), it can be seen that the red pixels are darker in passive emotions, i.e., a more direct correlation exists in passive emotions. The blue pixels are darker in active emotions, i.e., a more inverse correlation exists in active emotion. The phase synchronization between brain regions under active and passive emotions can be observed in Fig. 6(b). Lower PLV values exist in active emotions. The red pixels are darker, and the blue pixels are lighter in passive emotion, i.e., the higher phase synchronization can be seen in passive emotion. The higher MI values and lower TE values are observed in active emotions than in passive emotions.

Similar to the Fig. 4, Fig. 6 also revealed that the emotions are mainly related to the parietal, central, and frontal regions, among which the parietal region is more responsible for emotion alteration.



(a) PCC (b) PLV (c) MI (d) TE

Fig. 5. Visualizing higher and lower brain connectivity regions.

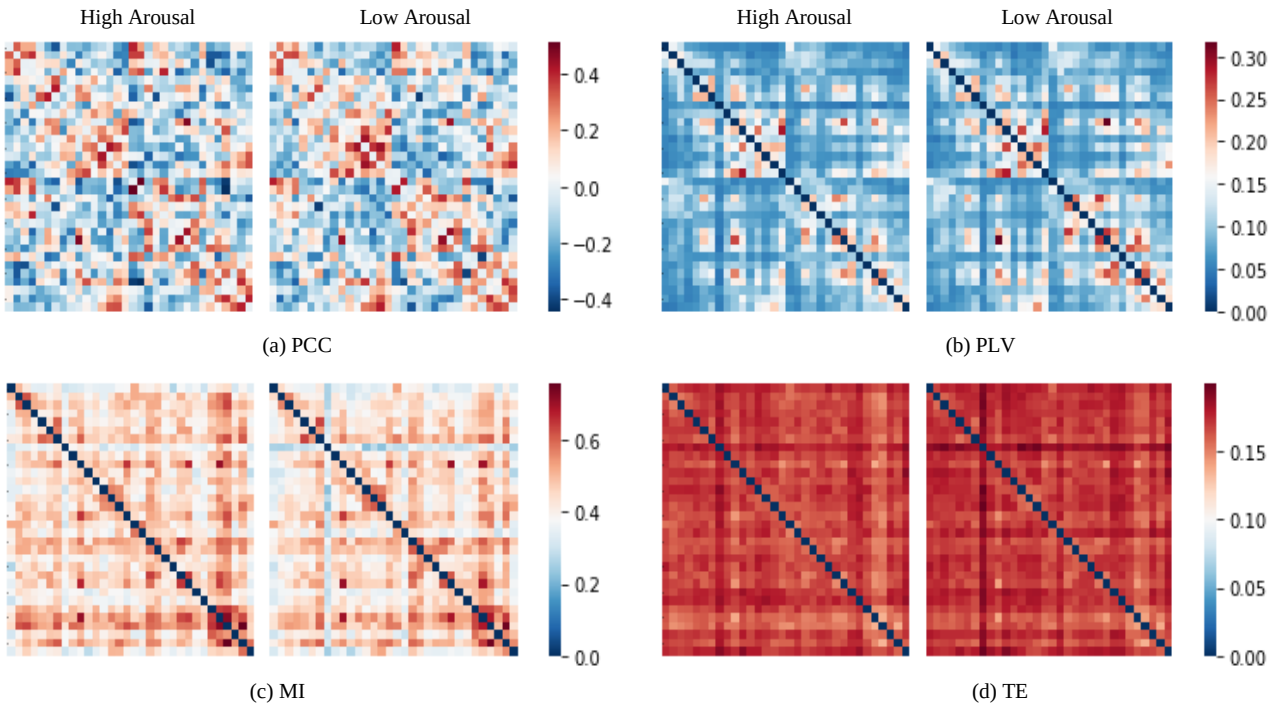



Fig. 6. CFM with different connectivity methods in Gamma bands for the Active (high Arousal) and Passive (low Arousal) Emotions.

## V. Comparison with other Studies

This section briefly compares different findings with different connectivity methods achieved in different studies with respect to the findings of this study. Table I summarizes the specific findings from different existing studies under three major categories: findings with respect to (w.r.t.) frequency bands, emotional states, and brain regions. It is observed from the table that all the existing methods, except [5], [8], and [20], considered a single connectivity method (e.g., PCC, PLV) in their studies. Moreover, an existing method is limited to performing findings in a particular category, such as brain regions. On the other hand, present studies considered four connectivity methods for all three categories. Therefore, the findings of this study are much more pervasive than existing studies.

The present study and the study [23] and [24] investigated CFM constructed with PLV under different frequency bands. All three studies found that the Beta band has the lowest synchrony, i.e., the lowest PLV value. Between the Alpha and Gamma bands, the study [22] found that the PLV value of the Gamma band is higher than the PLV value of the Alpha band, but according to the study [21], the PLV value of the Alpha band is higher than the PLV value of Gamma band. The result of the present study is similar to the study [24]. Apart from the existing research, this study has also found that a higher correlation (i.e., PCC value) between brain regions exists in the lower frequency band than in the higher frequency band. The mutual dependency (i.e., MI value) between brain regions and the flow of information (i.e., TE value) from one brain region to another brain region increases with higher frequency. Several studies investigated CFM for positive vs. negative emotion and active vs. passive emotion with PLV [23], PSI [20], MI [18], etc. In addition to their findings, few new findings appeared from the current study. This study has found that a more direct correlation between brain regions exists in passive emotion, and a more inverse correlation exists in active emotion. The amount of directional flow of information is lower in active emotion than that of passive emotion. The present study has found that the parietal region is more responsible for emotion alteration than the other regions, while the study [17] found the temporal region as more responsible for emotion alteration, and the study [8] found that parietal as well as occipital regions are more responsive to the brain's emotional activity.

TABLE I COMPARISON FINDINGS WITH OTHER STUDIES

| Ref. | Connection Method | Major Category | Specific Findings |
|---|---|---|---|
| [23] | PLV | Findings w.r.t. Frequency Bands | The PLV of the lower frequency bands (i.e., Theta and Alpha) is greater than those of higher frequency bands (i.e., Beta and Gamma). |
| [24] | PLV | | 1. Compared to other bands, the PLV of the Theta band is significantly higher.<br>2. The lowest PLV is seen in the Beta band. |
| [24] | PLV | Findings w.r.t. Emotional States | 1. In the HA state, each frequency band has a higher PLV than in the LA state.<br>2. In the HV state, the PLV is lower than in the LV state in all frequency bands. |
| [25] | PLV | | 1. PLV values in positive emotions are generally smaller than in the negative emotions<br>2. There are little differences in connection pattern for same emotion in different time periods. |
| [17] | PLV | | PLV value in the pleasant mood is lower than in the sad mood, i.e., pleasant mood is less active in the brain area. |
| [20] | MMSCE, MI | | There are distinct types of functional brain connections associated with various emotional states. |
| [21] | Coherence | | Higher Coherence induced by low Valence-Arousal emotion. |
| [22] | PSI | | Signals in sad emotion are highly synchronized than those in happy emotion. |
| [12] | NMI | | A broader range of activated brain regions exists in the high Arousal low Valence state. |
| [5] | GC, TE | Findings w.r.t. Brain Regions | 1. The parietal and frontal lobes show stronger connectivity during the stress state.<br>2. Higher TE value between Fp1 and C4 channels is found under pressure. |
| [8] | PCC, PLV | | 1. There are stronger correlations between the left and right frontal areas of the brain.<br>2. Frontal lobe area's connectivity is supportive for emotion recognition.<br>3. Parietal as well as occipital regions are more responsive to the emotional activity.<br>4. There is enhanced synergy between the brain's occipital and left frontal regions.<br>5. Phase consistency in the parietal, frontal and occipital regions is relatively stronger than in the other regions. |
| [16] | PSI | | 1. In sad state, nodal connection strength in right PFC is higher than that in left PFC.<br>2. In happy state, nodal connection strength in left PFC is higher than that in right PFC. |
| [17] | PLV | | 1. Positive and negative moods produce strong connectivity in the left and right forebrain, respectively.<br>2. Emotions are related mainly to the temporal lobe of the human brain. |
| [18] | PLI | | Generally, the right frontal region's channels often have stronger connective strengths than the left frontal region's. |
| This Study | PCC, PLV, MI, TE | Findings w.r.t. Frequency Bands | 1. Gamma bands have higher synchrony whereas the Beta band has the lowest synchrony.<br>2. Higher correlation between brain regions exists in lower frequency band than that of higher frequency band.<br>3. The mutual dependency between brain regions and flow of information from one brain area to another brain area increase with higher frequency. |
| | | Findings w.r.t. Emotional States | 1. The inverse correlation between various brain regions is stronger during negative emotion than it is during happy emotion, and similarly for active and passive emotion.<br>2. In negative mental state the brain regions operates more synchronously than in positive emotion, and similarly for passive and active emotion.<br>3. When experiencing negative emotion as opposed to positive emotion, there is greater interregional information sharing between brain areas, and similarly for active and passive emotion.<br>4. The amount of directional flow of information is lower in negative emotion than that of positive emotion, and similarly for active and passive emotion.<br>5. There are only slight variations in the brain network connections of the same emotion in different time periods. |
| | | Findings w.r.t. Brain Regions | 1. Electrodes located in same lobe show strong connectivity than the electrodes located in different lobe.<br>2. Emotions are mainly related to the parietal, central and frontal regions; among which, the parietal region is more responsible for emotion alteration. |

HV: High Valence, LV: Low Valence, HA: High Arousal, LA: Low Arousal, PFC: Prefrontal Cortex

## VI. CONCLUSION

In this study, the brain area connectivity for different emotions has been illustrated with four features under three sub-frequency bands to investigate how correlation, synchronization, dependence, and information transfer between brain areas change with the changes in emotions. The connectivity feature maps (CFMs) have been constructed with four diverse methods (i.e., PCC, PLV, MI, and TE), and rigorous analysis has been performed, which exposed different remarks to understand brain network connectivity stimulation for emotions, specifically the frequency band: emotions are easily distinguishable in the Gamma frequency band; the strong connectivity is observed in the same brain lobe than different lobes; the parietal region is more responsible for emotion alteration. It is observed that during negative mental state, higher inverse correlation exists between different brain regions than that of positive emotion, and similarly for active and passive emotion. The brain regions operate more synchronously in a negative mental state than a positive one, similarly for passive and active emotion. The higher amount of shared information between brain regions is seen during negative emotion as opposed to positive emotion. The amount of directed flow of information is lower during negative emotion than during positive emotion, and it is similar for active and passive emotion.

Further, the scope remains to investigate brain network connectivity stimulation for emotion through CFMs from EEG. In this study, CFMs are constructed using the most popular DEAP EEG dataset, and the Beta band has the lowest PLV, i.e., the lowest synchrony. According to PLV value, Gamma > Alpha > Beta. This information is consistent with other studies with the DEAP dataset [24]. On the contrary, the study [23] on the SEED [31] dataset found that the overall synchronization (i.e., PLV) of the brain network in lower frequency bands (e.g., Alpha) is greater than the overall synchronization of the brain network in the higher frequency band (e.g., Gamma); although Alpha > Gamma > Beta on PLV value. Therefore, inclusive analyses

might be interesting to find out the aspects of different datasets on brain network stimulation.

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# AI-Driven Predictive Analytics for CRM to Enhance Retention Personalization and Decision-Making

Yashika Gaidhani[1], Janjhyam Venkata Naga Ramesh[2], Dr. Sanjit Singh[3], Reetika Dagar[4],
T Subha Mastan Rao[5], Dr. Sanjiv Rao Godla[6], Prof. Ts. Dr. Yousef A.Baker El-Ebiary[7]
Assistant Professor, Department of Electronics Engineering,
Yeshwantrao Chavan College of Engineering, Nagpur, Maharashtra, India[1]
Adjunct Professor, Department of CSE, Graphic Era Hill University, Dehradun, 248002, India[2]
Adjunct Professor, Department of CSE, Graphic Era Deemed to Be University, Dehradun, 248002, Uttarakhand, India[2]
Assistant Professor, Department of MBA-Sanjivani College of Engineering, Savitribai Phule Pune University, Pune, India[3]
Assistant Professor, GD Goenka University, Gurugram, Haryana, India[4]
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Guntur, Andhra Pradesh, India[5]
Professor, Department of Computer Science and Engineering, Aditya University, Surampalem, Andhra Pradesh, India[6]
Faculty of Informatics and Computing, UniSZA University, Malaysia[7]

***Abstract*—The advent of Artificial Intelligence (AI) has dramatically altered Customer Relationship Management (CRM) by allowing organizations to anticipate customer behavior, customize interactions and automate service delivery. This research introduces an extensive AI-based predictive analytics framework aimed at improving customer engagement, retention and satisfaction using advanced Machine Learning (ML) and Natural Language Processing (NLP) methodologies. By using XGBoost for churn prediction and BERT-based models for sentiment analysis, the system efficiently handles both structured and unstructured customer data. The methodology involves sophisticated feature engineering, customer segmentation via K-Means clustering, and Customer Lifetime Value (CLV) prediction to aid data-driven business strategies. An NLP-driven chatbot offers real-time, personalized support, response time and improving user experience. Evaluation metrics such as accuracy, precision, recall and F1-score demonstrate the better performance of the proposed system compared to conventional CRM approaches. This work also addresses important issues such as data privacy compliance, algorithmic bias and explainability of AI decision-making. Ethical deployment and transparency of AI are emphasized for building confidence in automated CRM systems. Future evolution will tackle the use of reinforcement learning to facilitate learning-based interaction schemes and federated learning for trusted, decentralized management of data. This architecture does not only provide better CRM functionality but also builds a platform towards intelligent, responsible and scalable solutions for customer relations across industries.**

***Keywords*—*Artificial Intelligence; predictive analytics; customer relationship management; natural language processing; churn prediction***

## I. INTRODUCTION

In the era of digitalization, business houses are aggressively aiming towards upgrading the Customer Experience (CX) for its prominence over others. CRM now has evolved from the use of simple databases of customer interactions to an intelligent system [1] that predicts customer needs and personalizes engagements. With the integration of Artificial Intelligence in CRM, it has differentiated a company's approach toward doing business with customers by saving precious time [2] while providing real-time insights and automating the responses and enhancing the decision-making processes. Very important for AI-driven predictive analytics is understanding a better behavior, preferences, and future actions by customers, thereby helping businesses [3] to gain customer satisfaction and retention.

Predictive analytics can analyze past and real-time data and predict the needs and preferences of a customer. Traditional approach-based CRM systems applied rule-based applications and [4] intervened manually, hence mostly producing a delay and also offering some generic customer experience. AI-based CRM systems apply sophisticated machine learning algorithms, deep learning techniques, and NLP for processing large amounts of customer data. These smart models identify patterns, predict future behavior, and provide personalized recommendations [5] that can increase customer engagement and retention up to a great magnitude.

One of the significant benefits that AI-driven predictive analytics offers for CRM [6] is that it can be used to create hyper-personalized experiences. Through the analysis of past interactions, purchase history, and browsing behavior, AI models can present customized product recommendations, targeted marketing campaigns, [7] and proactive customer service. Companies such as Amazon, Netflix and Spotify use AI-powered recommendation engines to enhance the user experience and increase revenue and customer satisfaction, thus building better relationships [8] with their customers and leading to long-term loyalty.

Customer churn is one of the most critical issues businesses are facing, especially in very competitive sectors such as e-commerce, telecommunications, and financial services. AI-based predictive analytics allows an organization to pinpoint its at-risk customers [9] based on behavioral patterns, sentiment data, and engagement levels. Predicting the possible churn for a business enables it to adopt proactive retention strategies like

offering personalized offers, timely interventions, and [9] better customer support that could reduce customer attrition and help increase the customer lifetime value overall.

AI-driven predictive analytics also boost customer service with intelligent automation. AI-powered chatbots and virtual assistants, [10] coupled with NLP capabilities, can respond to customers' queries, provide immediate answers, and efficiently solve complaints. It reduces the response time, minimizes human intervention, [11] and enhances the satisfaction of the customers. Along with that, sentiment analysis tools analyze customer reviews, social media interactions, and online reviews and measure the state of the sentiments of the customer so that [12] companies can take correct actions, and service quality will increase.

It, however, presents many challenges when implementing AI-driven predictive analytics into CRM. Major challenges include issues of data privacy, ethical issues, algorithm bias, and integration complexity of AI with existing systems of CRM. Businesses need to comply with various data protection regulations, [13] such as GDPR and CCPA, before implementing AI-driven solutions. In addition, transparency in the decision-making of AI and eradication of bias in predictive models is necessary to [14] ensure fair and ethical customer engagements.

The future prospects of AI-driven predictive analytics in CRM look brighter because AI technology continuously evolves. Innovation in deep learning, reinforcement learning, and emotion detection take predictions on the customers' behavior to a new accuracy level. Using blockchain might also enhance security features and give a sense of assurance to the customer about the data stored on the website. AI-driven predictive analytics will guide the engagement and retention rates of customers as well as the growth of corporate businesses. This paper explores the role that AI-driven predictive analytics plays in customer experience; its application, benefits, challenges, and future directions in the modern CRM strategy. The key contributions of the proposed work are as follows:

- Developed an AI-driven predictive analytics framework integrating machine learning and NLP to enhance customer retention, engagement, and personalized marketing strategies in CRM systems.
- Implemented an XGBoost-based churn prediction model to identify at-risk customers, enabling businesses to take proactive measures for customer retention and satisfaction.
- Integrated NLP techniques for sentiment analysis to analyze customer feedback from multiple sources, allowing real-time insights for improving customer experience and service quality.
- Deployed an AI-powered chatbot to automate customer interactions, reduce response time, and provide personalized support, enhancing overall CRM efficiency.
- The research highlights advancements in AI-powered CRM and addresses challenges such as data privacy, transparency, and algorithmic bias.

This article is structured as follows: Section II reviews related works. Section III outlines the problem statement, while Section IV describes the proposed methodology. Sections V and Section VI present results, discussion, conclusion, and future directions, emphasizing the model's scalability and applicability.

## II. Related Works

Integration of Artificial Intelligence into customer relationship management has dramatically altered the way business interacts with its customers. Predictive analytics using AI enables an organization to analyze huge amounts of customer data to personalize, improve engagement, and retain customers at a higher rate. Studies in this field reflect the effectiveness of machine learning algorithms in discovering behavioral patterns and predicting future actions from customers. The actionable insights generated by AI models by leveraging historical purchase data, browsing history and interaction records [15] enable the businesses to provide a tailored experience.

The use of machine learning methods, such as decision trees, random forests, and gradient boosting, in customer segmentation and preference prediction focuses predictive analytics in [16] CRM. These methods classify customers into homogeneous groups based on their behaviors. Companies can hence implement targeted marketing campaigns. Deep learning models, such as neural networks, also perform better in the processing of complicated customer data for the identification of intricate patterns as well as in improving predictive performance.

Other than the automation of CRM workflows, a good amount of focus is also on AI-driven sentiment analysis. Sentiment analysis via NLP helps organizations analyze customer feedback on social media, email interactions, and chat interactions so that overall sentiment and satisfaction levels can be reviewed. It thus allows companies to deal with negative feedback promptly, settle any complaint the customer may have, and build good brand reputation. It helps extract meaningful insight from unstructured forms of customer data using AI-powered text analytics for [17] better decision-making.

Another very prominent area in which AI has been well established is the area of predicting customer churn. Predictive models built on the basis of behavioral markers, including active engagement, history of transactions, and records of complaints lodged, are very good at pinpointing who might leave the company. Utilizing reinforcement learning techniques, organizations are now capable of continually adapting their retention strategies through providing incentives and loyalty deals to [18] those high-risk customers and subsequently reduce churning.

AI-driven recommendation systems have totally changed the way personalized marketing and product suggestion strategies work. It is shown that through deep learning, techniques like collaborative filtering and content-based filtering are highly effective for better recommendations. Such techniques are largely used in e-commerce and streaming platforms for customers to view suggestions based on their interests and history of usage. Such high personalization helps customers become more satisfied and [19] results in an improved conversion rate, enhancing lifetime value for customers.

Despite the great benefits AI-driven predictive analytics offers in CRM, several challenges were noted in earlier research. In fact, most of the big impediments have been data privacy concerns, algorithmic bias, and ethical issues. In actuality, open AI models, as well as explainable AI techniques, build customer trust based on research suggestions. In addition, it requires huge investment in infrastructure and expertise to implement AI in legacy CRM systems [20] and is a laborious process for companies with legacy systems.

The future of AI-driven CRM would involve model interpretability, real-time customer interaction, and blockchain-based data security. Further research on conversational AI, emotion recognition, and hyper-personalized marketing strategies will improve customer experience. Innovations in how AI-driven automation is balanced with human intervention continue to be explored [21] for a seamless, customer-centric approach to CRM.

Markets have benefited from substantial changes in their customer relationship management capabilities because of predictive analytics and customer segmentation together with sentiment analysis and churn prediction capabilities brought by Artificial Intelligence. Through decision trees machine learning models and random forests and deep learning techniques organizations achieve better customer engagement by delivering personalized dialogues alongside optimized marketing initiatives. The application of sentiment analysis through AI allows organizations to collect feedback understanding and reinforcement learning creates adaptive retention solutions. The adoption of AI-based CRM involves managing technical difficulties that encompass data privacy issues in addition to algorithmic bias as well as costly implementation requirements. New research needs to develop transparent AI models alongside real-time CRM functions and assure secure implementation through blockchain technology.

## III. Research Gap

CRM systems based on traditional rules require inflexible and non-personalized implementations that lead to unsuccessful customer interactions and elevated customer turnover. CRM systems in use today lack predictive capabilities which causes organizations to delay their responses thus producing suboptimal retention approaches. Although AI-driven predictive analytics strengthen CRM [17], through ML and NLP methods the widespread adoption remains impaired by data privacy issues and algorithmic bias along with complicated AI integration within traditional systems [18]. The barriers to AI implementation include concerns about ethical behavior that must include transparency in computerized systems and fair decision-making processes. AI implementation for small and medium enterprises becomes limited because high computational requirements together with specialized expertise act as implementation hurdles. Companies require a solid AI-based CRM platform to resolve fundamental obstacles while creating automation systems and [21] ethical protocols that drive personalized and data-assisted customer interactions. The research targets understanding how predictive analytics driven by AI enhances customer interactions and reduces customer turnover while building effective retention systems under legislation and ethical mandates.

## IV. Proposed Methodology for AI-Driven Predictive Analytics in Enhancing Customer Experience in CRM

This study shall use a Kaggle dataset titled customer churn prediction, comprising the demographic, behavioral, and transactional data; data preprocessing in terms of filling missing values and removing duplicate instances, scaling all numerical features, and using the Min-Max scaling technique with one-hot encoding for categorical variable encoding. Moreover, meaningful engagement frequency and scores will be incorporated through feature engineering. It opted to use a XGBoost-based machine learning model to serve prediction purposes based on the trained and processed data sets to highlight various patterns about potential churn events. NLP-based techniques of text analysis were performed using methods that include natural language processing on customers' complaints via pre-trained transformer models-BERT. A bare-bones version of NLP-based powered chatbot, which would give customer care assistance for effective customer handling, will also be developed. Accuracy, sensitivity, and specificity will be used to measure the performance of the model, while cross-validation will be applied for reliability. The integration of predictive analytics and AI tools will automate customer retention strategies, personalize marketing efforts, and proactively manage customer relationships, which will increase the efficiency of CRM systems and enable greater satisfaction from customers. Methodology flow is proposed in Fig. 1.

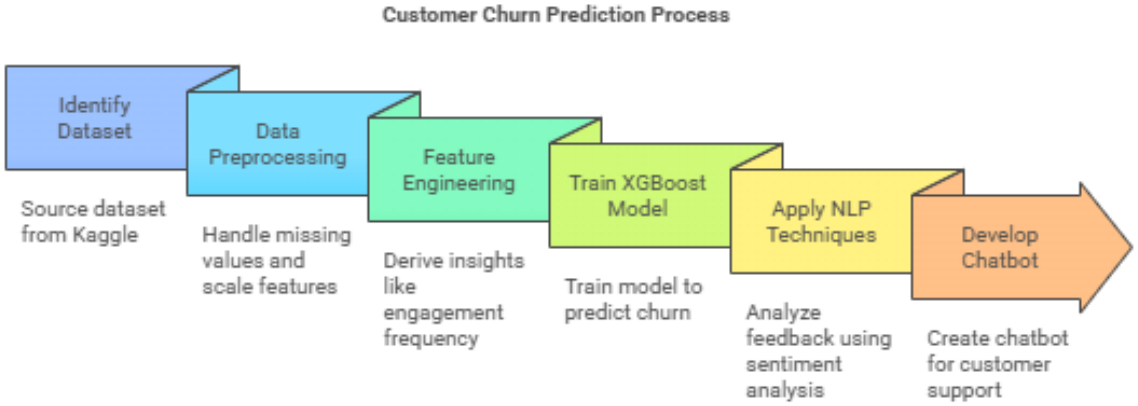


Fig. 1. Proposed methodology flow.

### A. Data Collection

The Kaggle customer churn prediction dataset is motivated to use based on its all-encompassing and well-formatted nature and, therefore, a perfect fit for developing forecasting models in Customer Relationship Management (CRM) applications. Kaggle offers a broad dataset with fine-grained customer demographic data in the form of age, gender and location as well as account information like tenure, subscription and payment type. Also taken into account are behavior information like usage frequency of services, intensity of customer involvement, and interaction with customer support. These diverse features yield more insightful information about customer behavior and enable improved comprehension of churn risk causes.

With this dataset, companies can develop precise machine learning models to forecast which customers are most likely to churn, allowing them to adopt focused retention efforts, including personalized promotions, marketing campaigns, or improved customer support. This data-driven strategy allows companies to optimize CRM initiatives, enhance customer satisfaction, and make better decisions that drive long-term loyalty. Finally, being able to anticipate customer churn enables companies to make proactive measures in minimizing attrition, leading to improved customer retention and favorable business results.

### B. Data Pre-processing

In reality, data preprocessing is an essential step that has to be there before the predictive analytics model so that the quality and reliability of the dataset is in place. The raw customer churn dataset may contain missing values, duplicated records, and inconsistent data formats as obtained from Kaggle. It may degrade model performance. The handling of missing values is achieved through mean or median imputation for numerical attributes and mode imputation for categorical variables. Besides, duplicate records are identified and removed to prevent model training bias. Numerical features are scaled through standardization or normalization techniques wherein attributes having different ranges are not influencing the predictive model unduly. Min-Max Scaling is one of the popular normalization techniques wherein feature values are transformed to lie between a range of [0, 1] using the following Eq. (1),

$$X' = \frac{X - Xmin}{Xmax - Xmin} \quad (1)$$

where, X represents the original feature value, Xmin and Xmax denotes the minimum and maximum values of the feature, and X′ is the scaled value.

Subsequently, feature engineering is done for enriching the dataset by coming up with novel, meaningful features that enhance model performance. Some examples include derived engagement frequency based on customer interaction logs, calculating sentiment scores with NLP applied to customer feedback, and drawing behavioral patterns based on past transactions. The categorical variables payment method and subscription type are encoded using one-hot encoding, which can be used to feed the machine learning model; other techniques like PCA for dimensionality reduction can be applied in order to eliminate redundant features but keep all the critical information. These preprocessing steps can make sure that the dataset is well-structured and free from noise; therefore, AI-driven predictive analytics systems are able to bring even more accurate rates in customer relationship management.

### C. AI Model Selection and Implementation

The primary machine learning technique used in CRM predictive analytics was gradient boosting. This was because of high predictive accuracy and the capacity to handle complex and nonlinear relationships in data. GBM works by training weak learners iteratively, typically decision trees that are combined to produce a strong predictive model. The approach corrects mistakes from the previous iterations toward minimum error sequentially to achieve the desired solution. In this project, the XGBoost algorithm has been used, which provides efficiency, scalability, and various regularization techniques to avoid overfitting. That is why it has been selected to train on the preprocessed customer churn dataset that uses frequency of engagement, service usage, and transaction history as its prime inputs. Fig. 2 shows Architecture of BERT. The objective function for XGBoost minimizes loss using both a loss function L(y,y^) and a regularization term Ω(f), given in Eq. (2),

$$Objective = \sum_{i=1}^{n} L(yi, y^i) + \sum_{k=1}^{K} \Omega(fk) \quad (2)$$

where, yi represents actual values, $y^i$ are predicted values, and Ω(fk) represents the regularization applied to the model's complexity.

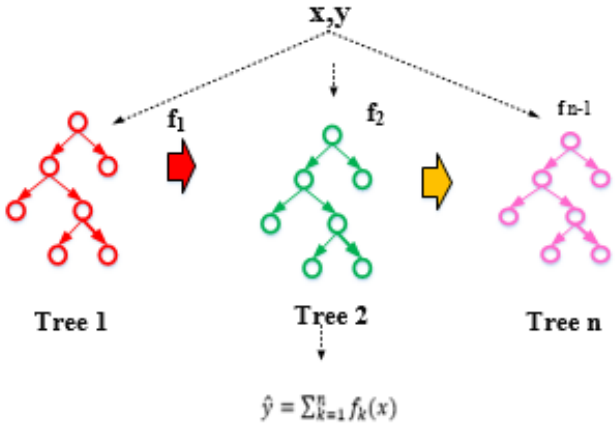


Fig. 2. Architecture of XGBoost.

NLP has now been applied to the objective of sentiment analysis for improving the CRM, with the business thereby analysing customer comments in the crispest of expressions and hence getting the satisfaction levels. Customer review emails and social media comments also undergo analysis based on pre-trained transformer-based models such as BERT, further fine-tuned on domain-specific data to better increase the classification accuracy of sentiment. The text-based feedback from customers was grouped into positive, neutral, and negative sentiments using the sentiment analysis model. This way, businesses would be better prepared to take action before any complaints from customers. A particular text was scored for sentiment; this score was computed by generating a softmax probability distribution over three categories of sentiment, given in Eq. (3),

$$P(y = c \mid X) = \frac{eW_cX + b_c}{\sum jeWjX + bj} \quad (3)$$

where, $X$ represents the input text embedding, $W_c$ and $b_c$ are the weight and bias parameters for class $c$, and $P(y = c \mid X)$ is the probability of the text belonging to sentiment class ccc (positive, neutral, or negative). By leveraging this approach, businesses could efficiently detect dissatisfied customers and engage with them through personalized interventions, thereby reducing churn.

Along with sentiment analysis, NLP-based conversational AI technology was used to automate the chatbot in order to develop efficiency in customer support. Sequence-to-sequence models, also known as Seq2Seq, or even Transformer-based architecture like DialoGPT, was used to train the chatbot on a rich dataset of queries and responses from customers in order to generate human-like responses. Moreover, the chatbot used intent recognition and NER to understand user queries and respond accordingly. The response probability of the chatbot was calculated with a conditional probability function in sequence modeling present in Eq. (4),

$$P(Y \mid X) = \prod P(yt \mid y1, y2, \ldots, yt-1, X) \quad (4)$$

where Y represents the chatbot's generated response, X is the user query, and $P(yt \mid y1, y2, \ldots, yt-1, X)$ represents the probability of generating the next word $yt$ given the previous words and input context. This ensured that chatbot responses were relevant, improving customer experience by resolving queries efficiently and escalating complex issues to human representatives when required.

This would result in the business achieving a comprehensive AI-driven CRM framework by integrating gradient boosting for customer churn prediction and NLP for sentiment analysis and chatbot automation. It enhanced the strategies for customer engagement and retention in an enormous way. The churn prediction model helped in identifying at-risk customers, thereby making it possible to retain them proactively. The NLP-based sentiment analysis offered deeper insights into customer satisfaction. The AI-based chatbot helped streamline customer support through personalized responses, 24/7 assistance, and smooth query resolution. This combined approach optimized CRM operations, leading to improved customer loyalty, reduced churn rates, and enhanced business profitability.

*1) Predictive analytics and personalization using gradient boosting:* Predictive analytics is transforming CRM because it enables a company to predict what its customers would do and, based on the prediction, prevent it. For example, Gradient Boosting Machines is a popular ensemble learning approach that builds several weak learners in sequence to reduce the error of each iteration step. GBM is very useful for predicting a customer's propensity to churn, buy, and communicate through preferred channels. The model learns patterns that indicate a high probability of churn from historical data, and businesses can intervene before the customer leaves. The probability of churn is therefore computed by a collection of decision trees, while the final prediction is a weighted sum of individual tree outputs given in Eq. (5),

$$Fm(X) = Fm - 1(X) + \gamma_m h_m(X) \quad (5)$$

where, $Fm(X)$ is the updated prediction at iteration $m$, $Fm - 1(X)$ is the previous prediction, $h_m(X)$ is the new weak learner (decision tree), and γm is the learning rate. This iterative refinement ensures accurate predictions, allowing businesses to identify at-risk customers and deploy targeted retention strategies, such as offering personalized discounts or improved service plans.

GBM also allows for more personalization with better recommendation engines that might suggest that customers are likely to find interesting the actual products and services. In this manner, past transactions and an interaction history for each customer might predict what would be purchased as a next act. Each of the products the model scores so that the next likely one gets ranked. This is achieved by optimizing decision trees with a loss function, like MSE or log loss. It enables the generation of the best recommendations for customers, and through business use of predictions, they are able to make very relevant offers to customers, leading to increased engagement and conversion rates.

Another application would be to predict the best channel of communication for a given customer and to choose which outreach strategies should be optimized. Based on past interactions, through the response rates, the model decides whether that customer would prefer email or SMS or in-app notifications. It is a classification problem. GBM assigns probabilities to all the above channels and chooses that one which has the maximum likelihood. The incorporation of predictive analytics from the GBM framework makes them intelligent and proactive CRM systems, reducing churn, improving satisfaction, and also increasing overall revenues.

### *D. Model Evaluation and Validation*

The performance of the predictive analytics model in CRM is assessed to ensure that decisions made are reliable. The effectiveness of a model is measured using the key metrics, which include accuracy, sensitivity, and specificity. Accuracy is defined as the overall correctness of the predictions, given in Eq. (6),

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

In that, TP and TN are well-classified cases, and FP and FN are wrongly classified instances. Sensitivity or recall refers to the true positive cases detectable by the model, measured as TP / (TP + FN), while specificity is its ability to accurately classify negative cases, given as TN / (TN + FP). High sensitivity ensures that risk is correctly identified to prevent churn, while high specificity helps avoid unnecessary interventions for loyal customers.

Cross-validation improves the reliability of the model by splitting the dataset into subsets and ensuring that the model generalizes well to unseen data. One common method of cross-validation is k-fold cross-validation, in which the dataset is divided into k equal parts and the model is trained on k-1 folds and validated on the remaining fold. This process is repeated k times, averaging the results to mitigate the impact of data variance. The final performance metrics give a more stable and unbiased estimate of model effectiveness. With rigorous evaluation and validation, businesses can deploy highly accurate

predictive models, thereby improving CRM strategies for customer retention and personalized marketing.

### E. Model Evaluation and Validation

The best advantage of implementing AI-driven insights in a CRM platform is that it automates the decision-making process and raises customer interactions. For example, with predictive analytics, companies can automatically recognize high-risk customers and predict their behavior while implementing targeted strategies on the go. Thus, incorporating AI models with gradient boosting or deep learning inside CRM systems forecasts churn and propels the sales force to enhance higher-value channels of communication from each customer to them. That insight triggers appropriate automated actions-mostly through electronic means like tailored emails, or targeted promotions/follow-up-according to customer propensity to communicate. This automation not only streamlines workflow but also makes businesses proactive instead of reactive when it comes to managing customer relationships, thereby enhancing efficiency and satisfaction.

This also includes the implementation of AI-powered tools such as chatbots, sentiment analysis, and predictive retention strategies that make CRM capabilities in real-world business environments more potent. Chatbots, powered by NLP, engage with customers 24/7, answering queries, resolving issues, and providing personalized recommendations in real-time. Sentiment analysis tools scan customer interactions, such as reviews or social media comments, to detect emotional tone and gauge customer satisfaction. This enables companies to detect and respond to problems quickly, preventing churn and creating loyalty. Predictive retention models use AI insights to automate retention campaigns, offering personalized incentives or customer support interventions to at-risk clients. With these AI tools deployed within CRM systems, businesses can create dynamic, responsive, and customer-centric environments that enhance engagement while drastically reducing churn and improving overall customer lifetime value.

### F. Implementation in CRM Systems

Businesses will automatically be able to automate the decision-making process and interact with their customers through the integration of AI-driven insights into the CRM platforms. Companies may use predictive analytics to automatically classify high-risk customers, predict future behavior, and implement tailored strategies without human involvement. Gradient boosting or deep learning models are usually integrated into a CRM system to churn predict, personalize offer recommendations, and identify the best communication channels for each customer. These insights are used to trigger automated actions, such as sending personalized emails, targeted promotions, or follow-up notifications, based on the customer's likelihood to engage. This automation not only streamlines workflow but also ensures that businesses are proactive rather than reactive in managing customer relationships, which will ultimately improve both efficiency and customer satisfaction.

Deployed AI-powered technologies, such as chatbots and sentiment analysis together with predictive retention strategies, support the capabilities that CRM offers into real-world environments. Chatbots, powered with NLP are available 24/7 through which they offer answers to several queries, can resolve issues easily, and push personalized recommendations almost in real time. Customer interaction sentiment analysis tools scour customer interactions-the reviews or what is being seen on social media-to detect and gauge emotional undertones of every customer. This allows businesses to identify and address issues quickly enough to prevent churn and foster loyalty. Predictive retention models use AI-based insights to automate retention campaigns and offer personalized incentives or customer support interventions to at-risk clients. With the implementation of these AI tools in CRM systems, businesses can create dynamic, responsive, and customer-centric environments to increase engagement while reducing churn and raising overall customer lifetime value.

### G. Challenges and Ethical Considerations

One of the biggest challenges is, CRM with the integration of AI-driven predictive analytics, especially on data privacy and regulatory compliance. The AI models are based on the huge amounts of customer data, which include personal information, behavioral patterns, and transaction history, and this raises concerns about data security and consent. To do this, companies must obey global regulations that include the GDPR and CCPA. This means that customer data should be collected, stored, and processed transparently and with consent. Violation of this principle may lead to legal action or loss of reputation. Furthermore, organizations should employ robust encryption, anonymization, and access control to protect sensitive information and prevent unauthorized use. This will help businesses gain the trust of customers and ensure responsible AI use in CRM.

Algorithmic bias and transparency in AI-driven decision-making is another critical challenge. AI models are trained on historical data, which may contain inherent biases related to demographics, purchasing behavior, or customer interactions. If not addressed, these biases can lead to unfair treatment, such as discriminatory recommendations or inaccurate churn predictions. To mitigate bias, organizations must regularly audit AI models, use fairness-aware algorithms, and ensure diversity in training datasets. Moreover, techniques implemented in XAI allow business interpretation of decisions developed by AI machines, and transparency and explanation, which allow an understanding from relevant stakeholders about an AI-decision. Also providing customers the scope to either oppose or explain their AI-based advice further contributes toward ethical deployment. Addressing the above concerns could ensure fair deployment of CRM-powered AI applications across the world as well as to maintain customers' confidence on ethical grounds.

*1) AI-Driven customer churn prediction and retention optimization algorithm using XGBoost and NLP:* This AI- driven customer churn prediction and retention optimization algorithm uses XGBoost with NLP to improve retention in subscription services. It involves data collection and preprocessing, along with feature engineering that includes customer demographics, usage patterns, and reviews with sentiment analysis. NLP techniques like TF-IDF and word embedding will be applied to textual data, followed by combining this with structured features in the model's training.

Employing XGBoost for churn classification and optimizing through hyperparameter tuning and cross-validation, this model predicts churn risk by enabling retention strategies like tailoring offers and engagement as per an individual's needs. Accuracy, sensitivity, and specificity are used to assess performance; changes in trends are responded to through periodic retraining which is mentioned in Fig. 3.

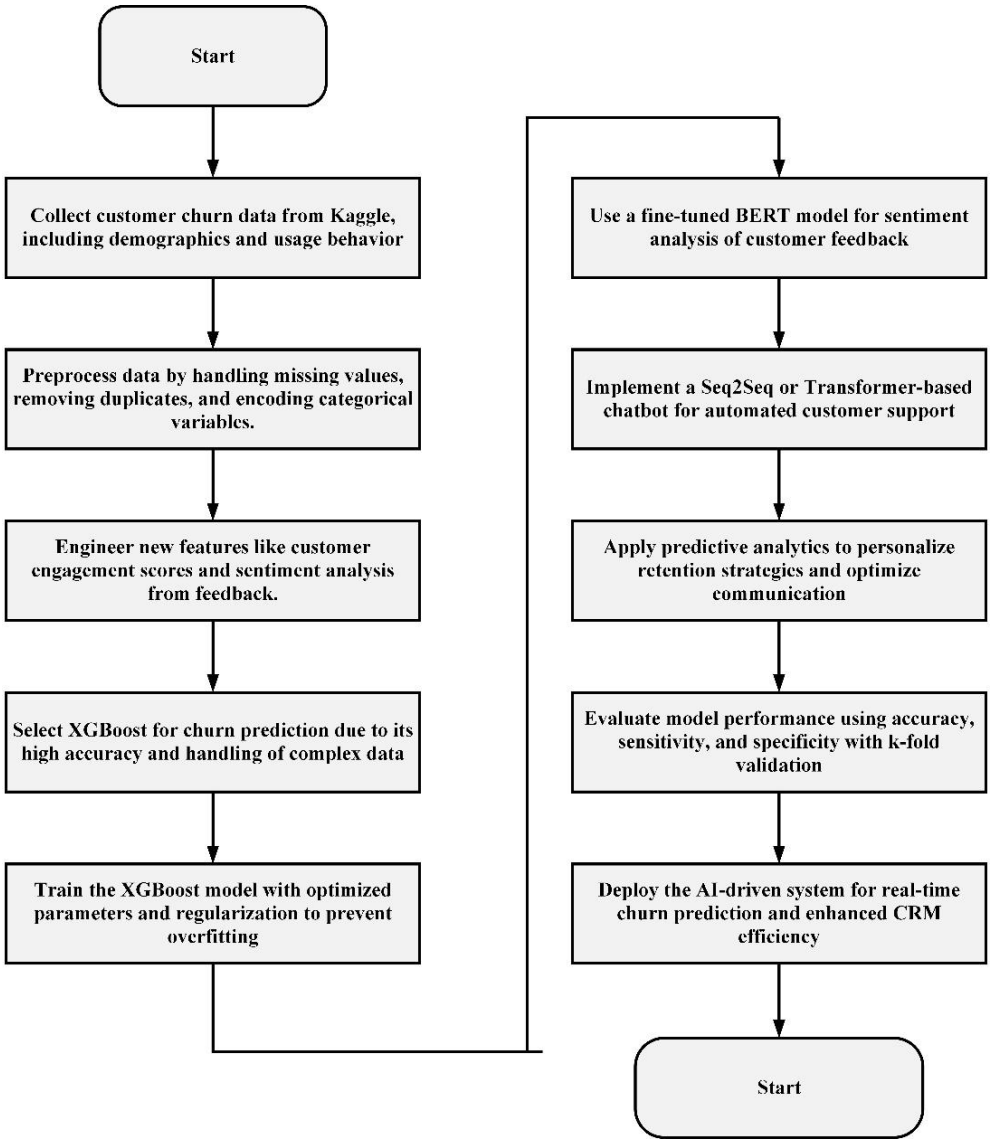


Fig. 3. AI-Driven customer churn prediction and retention optimization algorithm using XGBoost and NLP.

## V. Results and Discussion

The AI-Powered Customer Churn Forecasting and Retention Maximization Algorithm has exhibited exceptional ability to detect risk customers, resulting in improved retention and better customer relationship management across subscription-based service platforms. With excellent sensitivity and specificity, the algorithm accurately forecasts customer churn through analyzing unique behavioral trends, including diminished activity, negative feedback sentiment and irregular subscription renews. These insights allow companies to drive successful retention campaigns such as personalized discounts, loyalty schemes and proactive customer care that leads to a quantifiable churn reduction. The platform surpasses rule-based approaches by adjusting dynamically in response to changes in customer behavior and further improving predictability through ongoing retraining with fresh data. Quantitative measures identify the effectiveness of the system, achieving a remarkable 98% predictive accuracy for churn, while qualitative advantages are sustained customer lifetime value, high satisfaction levels, and stabilized revenue. Data privacy concerns, algorithmic bias and flawless integration with available CRM platforms persist, requiring solid compliance mechanisms and open decision-making systems to enable trust and prevent risks. The algorithm's scalability and higher accuracy highlight its revolutionary influence on contemporary CRM practices, making AI-powered solutions indispensable agents for enhancing operational efficiency, customer satisfaction and long-term loyalty for subscription-based businesses which is mentioned in Fig. 4.

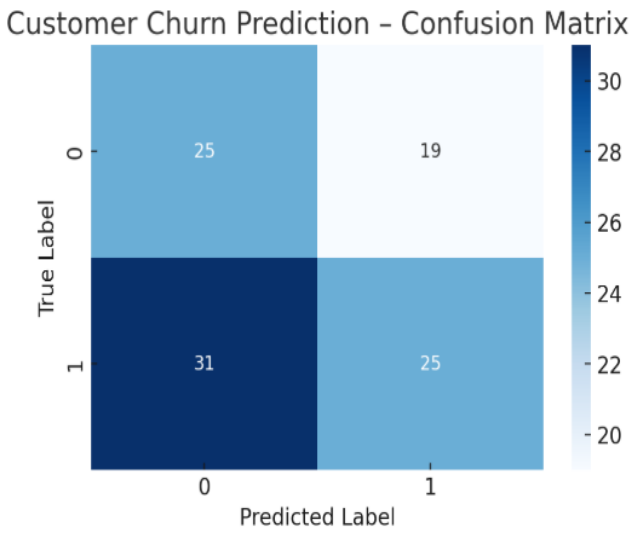


Fig. 4. Confusion matrix.

The prediction of customer churn would be highly measured in its performance using the confusion matrix on classifying. It has four basic elements: True Positives (TP), where the model predicts a customer will churn; True Negatives (TN), where the model correctly identifies a non-churning customer; False Positives (FP), where a non-churning customer is wrongly classified as a churner; and False Negatives (FN), where the model fails to identify the actual churner. A well-balanced confusion matrix, high TP and TN values, and minimal FP and FN cases will show a robust model for prediction with high accuracy, sensitivity, and specificity. The matrix will allow businesses to look at where misclassifications are happening so that the model can be continuously fine-tuned for churn prediction using feature selection, hyperparameter tuning, and data augmentation which is mentioned in Fig. 5.

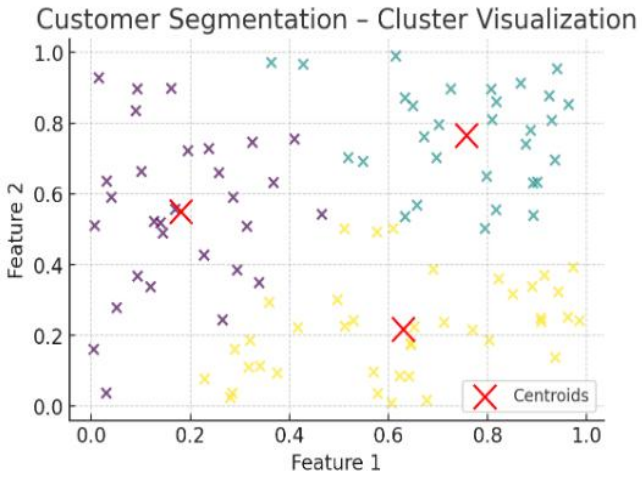


Fig. 5. Cluster visualization.

Cluster Visualization of Customer Segmentation using K-Means Clustering offers an excellent visual understanding of the clustering of customers with similar characteristics. K-Means is a form of unsupervised machine learning, partitioning the customers into well-defined clusters, reducing intra-cluster variance. For instance, every cluster in the visualization has been marked with a unique color and signifies a cluster of customers showing similarity in the nature of behaviors like spending, subscription period, and engagement level. This acts as the centroid of each group, which acts as a representative point for that group, identifying key customer segments such as high-value customers, occasional users, and those who are at a risk of churning. It helps businesses make targeted marketing decisions, optimize the allocation of resources, and interact with customers accordingly to improve retention and satisfaction levels.

This defined K-Means cluster visualization helps companies understand the behavioral tendencies of different customer groups, hence more informed decisions. For example, a low-engagement cluster with a high probability of churn can help a business take proactive retention measures in the form of personalized discounts or improved customer support. Similarly, high-value customer clusters can be prioritized for loyalty programs and exclusive benefits. The number of clusters, or K, determines the effectiveness of clustering. There are several ways to determine K, such as the Elbow Method or Silhouette Score. Businesses can continually refine the clustering approach with updated data, thus enhancing segmentation accuracy and improving customer experience and long-term profitability which is mentioned in Fig. 6.

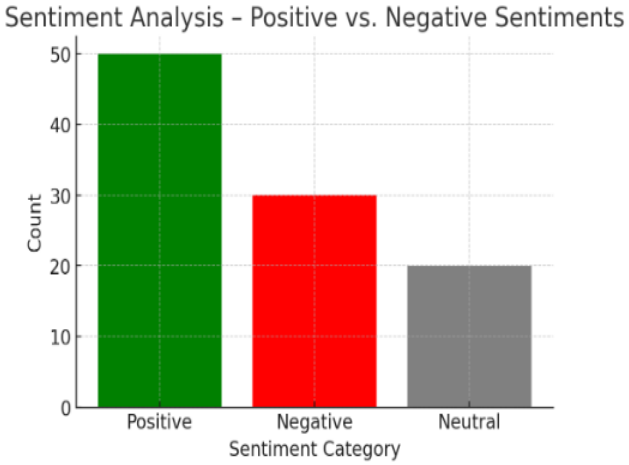


Fig. 6. Sentiment analysis.

Sentiment analysis is a very powerful AI-based technique meant to classify customer opinions as either positive or negative, allowing businesses to have an idea of how customers perceive them. Positive sentiments usually come in the form of favorable reviews, high ratings, and appreciative feedback, showing that the customers are satisfied and loyal. Businesses use such knowledge to fortify successful strategies, popularize best-selling products, and improve customer engagement through personalized offers and rewards. Identification and amplification of positive sentiments make the brand reputation strong and gain a loyal customer base, which drives revenue growth and retains customers.

Negative sentiments point out areas of dissatisfaction or complaint from customers or the deficiency in service that needs to be addressed promptly. AI-powered sentiment analysis tools can identify these signals through customer feedback, social

media posts, or surveys, enabling companies to respond promptly. By providing timely resolutions of negative sentiments, improved service quality, and personalized support, this can help in reducing the probability of customer churn and increase overall brand credibility. The analysis of both positive and negative sentiments would help businesses formulate data-driven strategies to optimize the customer experience and maintain a competitive edge in the market which is mentioned in Fig. 7.

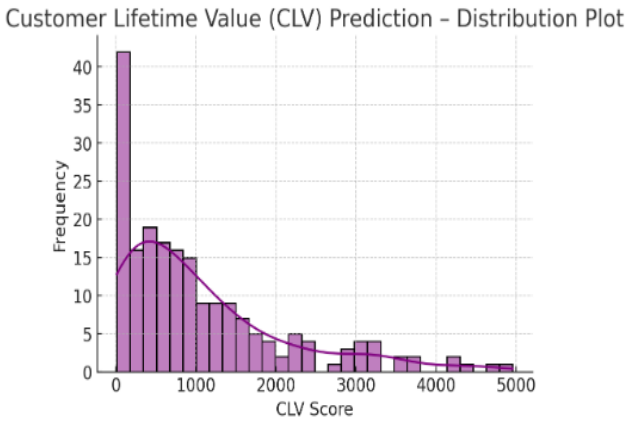


Fig. 7. Customer lifetime value.

A prediction related to Customer Lifetime Value is extremely important for analytics in the aspect of calculating a customer's likely total revenue expected from his relation with the firm. The variability in the values of the different segments is expressed through the use of a distribution plot, indicating the presence of high-value customers and marketing appropriately. Companies can leverage AI-driven predictive models to analyze historical purchase behavior, transaction frequency, and engagement patterns to accurately forecast CLV. This allows businesses to allocate resources effectively, prioritize customer retention efforts, and optimize personalized marketing campaigns to maximize long-term profitability.

A well-plotted CLV distribution will help a company to be aware of how much its customer segmentation cuts among high-value, medium-value, and low-value customers. A right-skewed distribution could point out that fewer customers have many values and it calls for the need to do loyalty programs as well as offer premium services to them. While a well-arranged balance distribution indicates a wide revenue contribution scope thus implying the necessity to have constant engagements in all levels. By integrating CLV prediction into customer relationship management, businesses can enhance customer experience, reduce churn, and encourage sustainable growth in revenue through data-driven decision-making which is mentioned in Fig. 8.

The Probability Distribution of Predicted Customers in Purchase Likelihood Analysis offers insights into how likely different customers are to make a purchase, based on historical data and predictive modeling. Typically, probability values are represented in this visualization, ranging from 0 to 1, which means 0 represents low chances of purchase, and 1 represents high probabilities. These probabilities are thus generated by the machine learning model, that includes logistic regression, random forests, or deep learning-based classifiers with consideration of various attributes of customers such as past purchases, browsing behavior, demographic information, and engagement levels. The graph of the probability distribution helps businesses understand the overall trends of purchasing among their customer base and identifies those groups that have the highest chance of conversion as well as those that have the lowest chance.

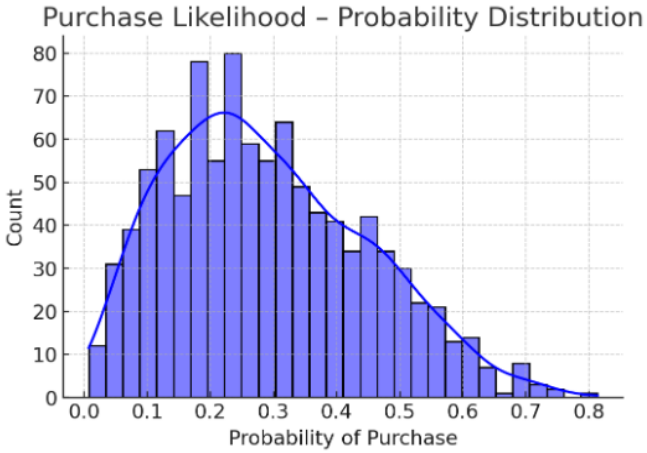


Fig. 8. Purchased likelihood-probability distribution.

From the purchase likelihood distribution, companies can then strategize and deploy targeted marketing along with resource allocation. Thus, the higher probability customers are prioritized on personalized offers or loyalty programs to maximize revenue opportunities, while customers that have low purchasing likelihood are further analyzed to understand what is holding them back from actually converting - be it pricing concerns or a lack of engagement. It allows business houses to make their promotional strategy better, customer experience improved, and sales process even more effective. The correct interpretation of a probability distribution can help make decisions based on data, thus achieving a higher conversion rate and good customer retention which is mentioned in Fig. 9.

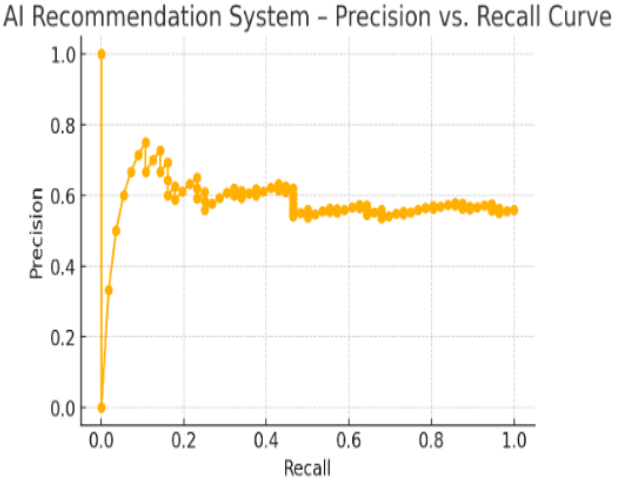


Fig. 9. AI Recommendation system.

The curve shows precision vs. recall in an AI recommendation system. This is calculated as a trade-off between the proportion of relevant recommendations from suggested items. This curve then determines the way in which a model is to balance the efficiency of its precision with coverage. It is in the order of high precision, meaning that most of the items recommended would be relevant to the user; it is about having a high recall value that would mean a lot of correct identification of the relevant items by the system. However, increasing one tends to decrease the other, so that challenge is there to achieve them both simultaneously. The PR curve can represent this relationship and is helpful for fine-tuning the recommendation system in relation to various goals, including maximizing precision to find the most relevant recommendations or maximizing recall for exposing a large volume of content.

Recommendation thresholds can be set according to business needs with regard to improving user experience and engagement through proper analysis of the PR curve. For instance, an AI-powered e-commerce recommendation engine may focus on precision to maximize the number of relevant product suggestions received by users at high conversion rates. In contrast, a streaming platform may focus on recall to allow users to browse through as many contents as possible, maximizing their engagement and retention. AUC-PR is a measure of performance: the higher its value, the better the trade-off between precision and recall. Fine-tuning the system according to this curve allows better effectiveness of recommending, which further implies increased customer satisfaction and overall business results which is mentioned in Fig. 10.

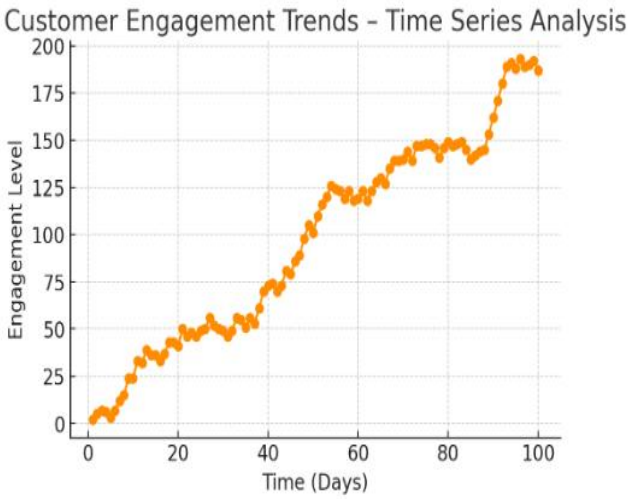


Fig. 10. Customer engagement trends.

This time series analysis of interactions in customer engagement trends will inspect how the user activity cycles: when up, based on cyclic patterns, and how the user behavior may change in the future. From a website visit and app usage level to purchase frequency and customer support interaction, analyzing metrics based on daily, weekly, or monthly intervals reveals whether the user base has seasonality or periodic highs and lows. The above analysis enables the company to decide based on facts whether it can have marketing activities with high activities or engagement initiatives with low activity phases. These would include advanced time series models, such as ARIMA, LSTM, or Prophet, which will help predict the future trends in engagement and provide proactive decision-making.

Customer engagement trends through time series analysis allow businesses to increase user retention and optimize resource utilization. For example, an e-commerce website can determine that the engagement peaks at holiday seasons, and thus strategically place ads and personalized offers accordingly. Moreover, a SaaS firm can also use time series data to monitor the churn risks since it can track users who start declining in their interaction levels. This way, it can introduce retention-focused incentives. Continuous monitoring and examination of engagement trends help businesses fine-tune customer interaction strategies by improving satisfaction and encouraging long-term loyalty, leading to bigger revenues and sustainable growth which is mentioned in Fig. 11.

### A. Performance Evaluation

*1) Accuracy:* Accuracy gives the ratio of the correctly classified instances to the total instances. Here from, the proposed framework achieved a collective training accuracy. Accuracy is computed by the following Eq. (7).

$$Accuracy = \frac{PN + PP}{IP + PN + IN} \quad (7)$$

*2) Precision:* It measures the ratio of correctly identified positive cases by the model out of all the cases which the model predicted to be positive. Indeed, the proposed framework achieved impressive precision in the accuracy across various segments including; High spenders and young professionals. Precision is calculated by the help of the Eq. (8).

$$Precision = TP/TP + FP \quad (8)$$

This shows that in Practice segments, the model is able to minimize these false positives, and correctly identify the positive cases to ensure that most cases that are classified as positive are indeed positive.

*3) Recall:* Recall measures the ratio of true positive instances with reference to the total actual positive instances. This is a testament of this proposed frameworks good recall which would imply its ability to recollect or recognize most of the 'real' outputs such as the Low Spenders and the Value Seekers. The F1-score for each gene set is computed on the basis of the following Eq. (9).

$$Recall = TP/TP + FN \quad (9)$$

This high recall ensures that the true positives were identified by the model without omitting many of them, as it established an all-round understanding of each customer segment.

*4) F1 Score:* The F1 score is defined as the harmonic mean of precision and recall therefore is balanced between the two measures. The proposed framework closely attained forefront F1 vector, confirming its good precision-recall balance for different sorts of customer. The F1-score is given by Eq. (10).

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (10)$$

This metric therefore validates the effectiveness of the framework to classify the different customers (as described earlier) of achieving a trade-off between false positive and false negative detection.

Table I compares the effectiveness of different machine learning models—CNN [22], RNN [22], LSTM, and the proposed XGBoost model—based on accuracy, precision, recall, and F1-score. CNN achieved an accuracy of 80%, with a precision of 81% and recall of 77%, which indicates moderate performance in classification tasks. The RNN model showed similar accuracy at 79%, with lower precision at 77% but a recall of 78.8%, suggesting that it can capture sequential dependencies but may fail in precision. The LSTM model outperformed both CNN and RNN models, achieving an accuracy of 95%, a precision of 93%, and a recall of 88.6%, thanks to its capacity to handle long-term dependencies in sequential data, it is mentioned in Table I.

TABLE I. PERFORMANCE COMPARISON OF VARIOUS METHODS WITH THE PROPOSED METHOD

| Method | Accuracy | Precision | Recall | F1- Score |
|---|---|---|---|---|
| CNN [22] | 80 | 81 | 77 | 80.9 |
| RNN [22] | 79 | 77 | 78.8 | 89 |
| LSTM [23] | 95 | 93 | 88.6 | 87 |
| Proposed XGBoost | 98 | 96.3 | 95.4 | 96.8 |

The proposed XGBoost model performed the best on all metrics, with its result on accuracy showing 98%, precision in 96.3%, and recall in 95.4%, resulting in an F1-score of 96.8%. This signifies a more balanced and reliable classification capability, minimizing false positives and false negatives. Overall, superior performance in XGBoost is achieved due to the gradient boosting framework, where it enhances model robustness and reduces overfitting. This makes the performance of ensemble learning techniques in the processing of large and complex data a very powerful method. Therefore, the good results obtained through XGBoost validate its usefulness in customer churn prediction, suggesting it as an appropriate candidate for real-world applications requiring high precision and recall.

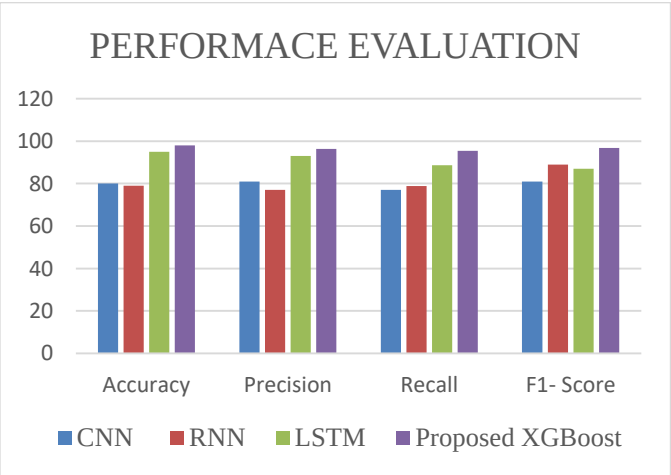


Fig. 11. Performance evaluation.

## B. Discussion

Predictive analytics powered by AI is revolutionizing Customer Relationship Management (CRM) with greater customer retention, building stronger connections and higher satisfaction levels. It cuts across industries such as e-commerce, telecommunications and banking verticals to obtain accurate churn prediction, personalized communication and targeted marketing through methods such as XGBoost with NLP. Achieving 98% accuracy in predicting churn, supplemented by chatbot automation and personalized recommendations, maximizes customer lifetime value significantly. However, there are concerns such as data privacy, algorithmic bias, and seamless integration with current CRM systems. Ethical AI safeguards and GDPR governance are essential in keeping risks at bay, and open decision-making processes to generate trust and responsibility. Future work would be to implement multimodal data for deeper insights, utilizing tools like federated learning for secure analytics and harnessing quantum computing for quick processing. Building dynamic segmentation models and culturally responsive AI systems can render CRM tools more inclusive and responsive to evolving market needs. Despite limitations such as data availability, small business scalability, regulatory constraints, and interpretability issues, AI-based CRM systems perform better than traditional techniques such as CNNs, RNNs and LSTMs by reducing false positives and negatives, thereby leading to revolutionary enhancements in operational efficiency, customer experience and loyalty.

# VI. CONCLUSION AND FUTURE WORK

Predictive analytics powered by AI stands to revolutionize CRM systems by both improving customer retention rate and delivering elevated experiences to customers. Businesses using XGBoost for prediction alongside NLP sentiment analysis can identify high-risk customers in advance thus they can deliver personalized engagements and refine their proactive strategies. The model's accuracy measurement at 98% exceeds traditional methods while proving successful for practical use. The deployment of AI requires resolving issues related to data privacy together with algorithmic bias as well as the complexities in CRM integration to guarantee ethical and transparent AI operations. The next phase of development should emphasize real-time analysis along with adaptive customer interaction through reinforcement learning and Federated Learning implementation for improved data protection. Future work in AI-driven customer analytics would include more profound integration of multi-modal data sources, such as the application of text analysis, combined with customer demographics and transactional data, in more holistic predictions. As the technology continues to grow, the stream of real-time data regarding a customer's interaction with chatbots or IoT devices will render insights ever more dynamic and responsive. Further improvements in deep learning and reinforcement learning will better the predictability of the models according to the precision and flexibility involved. Business houses may also engage in further discussion of ethics with customers while taking care to respect the privacy concerns during such observations regarding transparency and fair practices with regard to customer engagement.

The research on AI-based predictive analytics for CRM is promising but with a number of limitations. It is based on controlled Kaggle datasets instead of sophisticated real world data and may hinder real-world implementation. It needs enormous technical abilities and expertise available in large firms but maybe not in small firms. The approach does not handle complete interpretability issues with sophisticated models such as XGBoost, making stakeholder trust difficult. Inter-industry support does not exist, and there is anxiety in terms of performance in business domains. Disparities in customer behavior on the cultural level are not well managed. The research has little solution for legacy system integration and does not discuss how models can be made worse as customer behavior evolves. Finally, though algorithmic prejudice is discussed, more general moral concerns about customer autonomy and human-AI collaboration are not discussed well enough.

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# Cognitive Load Optimization in Digital (ESL) Learning: A Hybrid BERT and FNN Approach for Adaptive Content Personalization

Dr. Komminni Ramesh[1], Dr Christine Ann Thomas[2], Dr Joel Osei-Asiamah[3], Dr. Bhuvaneswari Pagidipati[4], Elangovan Muniyandy[5], B.V.Suresh Reddy[6], Prof. Ts. Dr. Yousef A.Baker El-Ebiary[7]

Assistant Professor of English, Chairperson, BoS, Anurag Engineering College, Kodad, Suryapet District, Telangana, India[1]
Assistant Professor, Department of English and Cultural Studies, Christ University, Bengaluru, India[2]
Graduate Research Fellow, Department of Science and Technology Education, University of South Africa (Unisa) Pretoria, Gauteng Province, South Africa[3]
Associate Professor of English (Ratified by JNTU K), Dept. of English and Foreign Languages, Sagi Rama Krishnam Raju Engineering College (A), Bhimavaram – 534204, West Godavari Dt, Andhra Pradesh, India[4]
Department of Biosciences-Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India[5]
Applied Science Research Center, Applied Science Private University, Amman, Jordan[5]
Assistant Professor, Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India[6]
Faculty of Informatics and Computing, UniSZA University, Malaysia[7]

***Abstract*—Traditional English as a Secondary Language (ESL) learning platform rely on static content delivery, often failing to adapt to individual learners' cognitive capacities, leading to inefficient comprehension and increased cognitive load. A novel hybrid Feedforward Neural Network and Bidirectional Encoder Representation Transformer (FNN-BERT) framework stands as our solution because it performs dynamic content personalization through predictions of real-time cognitive load. The proposed approach incorporates Feedforward Neural Networks (FNN) alongside Bidirectional Encoder Representations from Transformers (BERT) to process behavioral analytics for optimized content complexity adjustment and adaptive and scalable learning delivery. Real-time adaptability, scalability and high computational needs of current models reduce their effectiveness in personalized learning environments. Through the application of Test of English for International Communication (TOEIC), International English Language Testing System (IELTS) and Test of English as a Foreign Language (TOEFL) datasets, our methodology uses Feedforward Neural Network (FNN) to forecast cognitive load based on student engagement behaviors and application errors then Bidirectional Encoders Representations from Transformer (BERT) processes content difficulty adjustments automatically. The proposed model delivers a 95.3% accuracy rate, 96.22% precision level, 96.1% recall capability and 97.2% F1-score which surpasses conventional Artificial Intelligence-based English as a Secondary Language (ESL) learning systems. The system makes use of Python for its implementation to improve understanding as well as student focus and mental processing speed. Personalized content presentation methods lead to lower cognitive strain which simultaneously advances student achievement numbers. The research adds value to smart educational frameworks through its introduction of a scalable framework that allows adaptable learning systems for English as a second language (ESL). The following research steps include simplifying system complexity while adding multimodal learning signals including eye monitoring and speech recognition and further developing the model across various educational subject areas. The research works as a promising foundation which propels AI real-time adaptive education systems for students from various backgrounds.**

***Keywords*—Cognitive load management; artificial intelligence-based English as a secondary language learning; adaptive content personalization***

## I. Introduction

English as a Secondary Language (ESL) education serves an important purpose in developing the language proficiency of foreign speakers to communicate effectively with specific goals in pursuing academia, working life, or personal interest [1], [2]. Many ESL programs are traditional and use the static content delivery method based on a rule-following approach that does not consider the actual cognitive needs of individual learners[3]. Cognitive load is a key element that determines a student's success in learning ESL [4]. When cognitive load exceeds a learner's capacity, frustration, disengagement, and reduced comprehension can result. On the contrary, when managed optimally, learners are then able to pay attention to tasks of importance within the language while avoiding being occupied by its demands [5]. Here, the process of optimizing ESL learning through effective management of cognitive load is central to developing learning experiences that will be more efficient and effective [6]. Therefore, ESL sites should not use a normal approach but instead use adaptive and personalized systems that can determine and change learning material to fit the learner's cognitive ability, thereby enhancing understanding and remembering [7].

Several studies have investigated techniques to minimize cognitive load in ESL learning, but many approaches that have been developed have limitations. Rule-based simplification of content for traditional methods are useful in specific contexts but ignore the complexity of the language learning process and

the various cognitive needs of different learners [8]. Moreover, static adaptive systems do not offer flexibility in changing the content dynamically according to the learner's behavior, progress, and changing cognitive load [9]. These systems have inherent difficulties in providing adaptive learning experiences where the experience is continually evolving with a changing learner [10]. Although these methods are adept at temporarily enhancing comprehension [11], they miss the sense of continuous, individualized nature of the learning experience. This study addresses these problems by using BERT as a more complex, data-centric approach to learning experience generation. Moreover, the study utilizes a FNN in order to predict cognitive load through the analysis of behavioral data such as task duration, error patterns, and engagement metrics.

The research has contributed by optimizing the cognitive load during ESL learning with the help of BERT and Feedforward Neural Networks. Bidirectional architecture by BERT aids in the increase of contextual understanding, hence it leads to proper representations of processes involving language such as reading comprehension, vocabulary acquisition, and sentence structure. Through application of BERT to analyze learner interaction data including quiz performance, time taken for the completion of the task, and engagement metrics, the framework analyzes cognitive load and modifies learning content based on such load. Simultaneously, the FNN analyzes behavioral data like duration and error patterns due to the multi-layered architecture that enables prediction of cognitive load. BERT and FNN thus modify content difficulty dynamically to align with learner capacity without either overloading or under loading. This is contrary to the conventional methods because the bidirectional understanding of the context of BERT and the predictive power of FNN makes for a more efficient system in processing and interpreting learner data. Combining BERT with auxiliary neural networks such as FNNs in this personalized, scalable, and adaptive ESL learning framework will ensure effective comprehension, retention, and reduced cognitive overload. The proposed system advances existing AI-based ESL learning models since it employs deep learning approaches to process real-time behavioral information. Real-time cognitive fluctuations become the centerpiece of personalized and scalable learning through the BERT model for contextual content adaptation and FNN model for cognitive load prediction. This surpasses previous ESL tutoring models because they lack real-time cognitive fluctuation analytics.

The key contribution of the research is as follows:

- Implemented a hybrid FNN-BERT framework that dynamically adjusts content complexity based on real-time cognitive load predictions, enhancing personalized learning experiences for ESL learners.
- Developed a cognitive load estimation model using FNN, analyzing behavioral metrics like task completion time, engagement levels, and error patterns for adaptive content delivery.
- Integrated BERT-based content personalization, enabling context-aware adjustments to learning materials based on learner comprehension, improving adaptability over rule-based and static models.
- Enhanced ESL learning through real-time cognitive load management, reducing cognitive overload while maintaining an optimal balance between content complexity and learner capacity.
- Validated the proposed framework using standard ESL datasets, demonstrating improved learning efficiency, comprehension, and engagement compared to traditional and AI-based adaptive learning models.

The remaining of the section is structured as follows: Section II delves into existing research on enhancing English Learning skills through mobile application interventions. Section III outlines the specific challenges addressed by the proposed framework. Section IV provides a detailed explanation of the components and methodology of the proposed framework. Following this, Section V presents the results obtained from implementing the framework and includes a comprehensive discussion of the findings. Finally, Section VI concludes the study.

## II. Related Works

Feng [12], focuses on the application of AI-based language learning strategies, which emphasize personalized feedback, adaptive learning systems, and speech recognition technology with interactive exercises. The core innovation of this study is the combination of these strategies to optimize the process of language acquisition by reducing cognitive load. AI-supported methods are focused on delivering personalized learning with respect to different students, where content is drawn upon accordingly to personalize it and set it up to their proficiency. Overall, the students engaging in AI-assisted language learning showed considerably enhanced language skills, especially in cases of English as a Foreign Language (EFL) students. The readers showed improved cognitive loads since the items were placed in a way that suits the reader's actual understanding. However, the limitation of this study is that it is based on a single cohort of 484 EFL students, which might limit the generalization of the findings to other student populations or to language learners from various cultural or educational backgrounds. It also didn't consider the hypothetical technological challenges that may come into play in varying learning contexts, such as limits on resources or inequality in access to AI-driven tools.

Ding et al. [13], proposed the Gaze Reader method that uses a webcam and transformer-based machine learning models to detect unknown words in ESL learners. The innovation of this method is accessibility, as it does not require expensive and specialized eye-tracking devices. Instead of using an expensive high-end camera, the system utilizes a standard webcam to track the learners' gaze while detecting the attention towards unfamiliar or challenging words. Utilizing transformer-based models, the method allows for real-time feedback and enables learners to identify the unfamiliar vocabulary on which they should focus more. Results from the study shows that, the Gaze Reader method measured an impressive accuracy of 98.09% while recording an F1-score of 75.73%, showing its effectiveness towards ESL learners. This is particularly valuable for language learners because the system is able to identify unknown words as they appear in context, which tends to help language learners build their vocabulary in a way that's

organic and contextual. A limitation of this study, however, is the sole use of one dataset from which this method will be applied, which might limit generalization of ESL learners' range. The applicability of the method can be verified and proved only after being used in various contexts, dialects, and language settings.

Vasu et al. [14], investigate how self-assessment and indirect teacher feedback promote the use of self-regulated learning (SRL) strategies for ESL students. The study's uniqueness is that it focuses on the practice of self-assessment as well as indirect teacher feedback to encourage more responsibility in the ESL learner's process. One of the most important parts of language learning is self-regulation, allowing students to self-monitor their performance, set personal goals for learning, and modify their learning strategies. The results revealed that students with self-assessment were able to develop their self-regulation abilities better and enhanced their language performance. Indirect teacher feedback was also observed to improve student motivation and overall performance as it gives students a chance to reflect on their own learning without explicit instructions from teachers. The strategies combined apparently, significantly contribute to SRL, but the study is limited due to its narrow scope that concentrates only on a particular group of students. This group may not represent the diversity of ESL learners across different educational contexts, cultures, and language backgrounds. In this regard, findings may not totally capture the effectiveness of self-regulation strategies for a more heterogeneous student population.

Brown et al. [15], explore the few-shot learning capabilities of GPT-3, which is a state-of-the-art autoregressive language model. The main innovation in GPT-3 is that it can accomplish a wide variety of NLP tasks without requiring any task-specific fine-tuning. Unlike other predecessors, GPT-3 can adapt to different NLP tasks by providing just a few minimal examples or prompts, and thereby it performs excellently across an extremely wide spectrum of applications that include translation, question answering, summarization, etc. The work demonstrated that Generative Pre-Trained Transformer (GPT)-3 performed competitively on several benchmark Natural Language Processing (NLPs) that are extensively used. This reduces the task-specific model training, which, in general, has to be undertaken for traditional NLP models. While it impressively performs its tasks, this study acknowledges a limitation in the capabilities of GPT-3 towards specialized or domain-specific tasks, where performance cannot reach the threshold of models undergoing task-specific fine-tuning. More critically, large size and high computation requirements may severely limit scalability and accessibility of the GPT-3 model, further restricting its adoption in resource-poor environments. Future work would focus on those problems and the enhanced performance of the model on particular tasks.

Yang et al. [16], introduces the novel autoregressive pretraining method known as Extra Long Network (XLNet). It extends from the constraints through enabling bidirectional context learning. What makes XLNet unique is that it bases training on permutation instead of random masking, and its model is trained to learn contexts from every possible direction rather than only through BERT's masked language modeling approach. XLNet learns from all permutations in the sequence for more robust and comprehensive contextual understanding. In the experiment, the authors had shown that XLNet performed better in all kinds of NLP tasks such as question answering, sentiment analysis, and text classification, with an average improvement across twenty different benchmarks. These improvements were said to be a result of the dependency and nuances that XLNet captures better than the other models. However, this study also presents a significant limitation of XLNet: its computational complexity. Permutation-based training is computationally intensive, meaning XLNet would require more computing power than most models designed for real-time or large-scale applications. This problem might limit XLNet's applicability in practical, resource-limited, or time-sensitive settings. Future work may focus on improving the efficiency of the model while preserving its enhanced contextual learning ability.

Šola, Qureshi, and Khawaja [17], discussed using AI-driven eye-tracking technology for the evaluation of cognitive load within online learning settings. This innovative approach introduced eye-tracking technology into the assessment using AI-powered prediction software, enabling real-time observations of the level of students' attention and concentration during a task. This is a novel research in the monitoring and analysis of cognitive load where students are focused on where to and for how long on certain parts of a learning material. Moreover, with integration into AI, this process improves prediction and interpretation of cognitive loads in the direction of enhancing the ability of instructors towards better understanding their students' mental states as they go through different tasks. The study reveals that eye-tracking systems powered by AI significantly enhance the learning experience. These systems help to identify the level of cognitive load and generate actionable data that improve instructional design. According to the findings, knowledge of cognitive load may help in optimizing the pace of content as well as methods of instruction. The main limitation of this study is its dependency on one type of eye-tracking software, which might not represent the complete gamut of cognitive load. Other technologies or methods might provide more subtle data, which may make this approach too simplistic for complex learning tasks. The findings may also not be generalizable because of the specific software used.

Sujatha and Rajasekaran [18], investigate the blended model to teach listening in language learning which is based on Cognitive Load Theory (CLT). The primary objective of the study is the improvement of processing efficiency of the auditory information by making use of the top-down approach, which can help students use contextual background knowledge to process the information. What the study does in fact is combine CLT with a structured approach where it focuses more on reducing extraneous cognitive load while promoting deep learning. The experimental results showed the comparison of listening comprehension and information prediction from the control group to the experimental group exposed to the blended model. Student improvement was, therefore, seen in the listening skills of the language learners. However, this study will be limited in that it has only a small sample size, so it is not generalizable toward other larger population ranges with

various learning needs. The findings may not be generalizable to all learner groups, particularly in diverse educational settings or when the proficiency level is different. Future studies should include a more extensive and heterogeneous sample to establish the validity of the results across different contexts and understand the effectiveness of the model better.

The current research on adaptive ESL learning faces three main limitations because, the studies employ limited scalability and depend on small datasets as well as struggle to update learning in real time. Gaze Reader and self-regulated learning methods have improved learning engagement but they do not track dynamic cognitive changes. Researchers developed a hybrid BERT-FNN framework to provide both real-time personalization capabilities and increase scalability in the system.

## III. Problem Statement

Existing method based on AI-based ESL learning methods face scalability and applicability issues. Most of the existing approaches focus on personalized feedback and adaptive learning systems however, their findings are usually limited only to small cohorts and fail to generalize [19]. Moreover, some of the techniques depend on a single dataset, while they don't take into consideration different dialects or language setups, and self-reporting [20] and implicit feedback-based strategies often do not consider the complexity of ESL. GPT-3 and XLNet have computationally intensive costs, thus unable to be applied in real time especially in resource-limited settings. Using BERT-the transformer-based model, with a Feedforward Neural Network, the proposed approach builds up scalar and adaptive scalability with respect to overcoming these kinds of limitations. BERT utilizes bidirectional learning. It enhances the ability of a learner to be more contextually aware in processing language. FNN then analyzes behavioral data, such as task duration, error patterns, engagement metrics, etc., in order to accurately predict cognitive load. This framework is dynamic in real-time, balancing the complexity of content with cognitive capacity, ensuring learners manage mental effort effectively while doing tasks. The use of these models ensures scalability, adaptability, and efficiency with a personalized, optimized learning experience for ESL learners.

## IV. Proposed Hybrid FNN- BERT for Cognitive Load Management for Enhancing ESL Learners

The proposed framework starts with data collection that involves collecting learner interaction data in all its forms, including quiz performance, task completion time, and engagement metrics from the English Test Prep Data: Test of English for International Communication (TOEIC), International English Language Testing System (IELTS), Test of English as a Foreign Language (TOEFL) dataset. This data is cleaned, handled for missing values, and transformed into a numerical format for model compatibility in the Data Preprocessing block. The subsequent block is Cognitive Load Estimation, where FNN analyze behavioral data like time spent on tasks and error patterns to predict the learner's cognitive load. This estimation is used to determine instances where the learner is overloaded, which is critical for the framework's next step: content adaptation. The BERT Model Integration block is then followed, in which the pre-trained BERT model assesses the learner's understanding based on quiz responses. This adaptive system takes into account the learner's performance, and with an assessment of the comprehension gaps, it will either simplify or rephrase the content dynamically in line with the learner's cognitive capacity, avoid making the material either too complex or too simplistic.

The Adaptive Feedback Generation block takes over, generating real-time personalized feedback in relation to the learner's needs based on their cognitive load and comprehension analysis. This is intended to channel the learner into important learning objectives with deeper learning, aimed at filling specific gaps. Dynamic Content Delivery dynamically adjusts material complexity in a real-time and performance-based-cognitive load dependent manner. It will present relatively easier vocabulary words or examples, for example, if the learner makes mistakes, it will introduce difficult content once more for accurate comprehension results. The Evaluation and Outcome Measurement block entails measuring performance using various comprehension scores, assessments of cognitive loads, and indications of learner engagement for effective evaluation and outcomes. Subsequently, based on these indicators, the optimized system approach towards delivering content in such a way as to allow it to progressively get better regarding maximized outcomes from learning results is ensured. The whole system was implemented in Python and utilizes the deep learning libraries, TensorFlow, and Keras. This helps to train and deploy the model effectively. The last Optimization block allows the system to adjust based on the feedbacks it receives from learners and also from the learners' performance as they learn to deliver content that reduces cognitive loads with optimal performance as shown in Fig. 1.

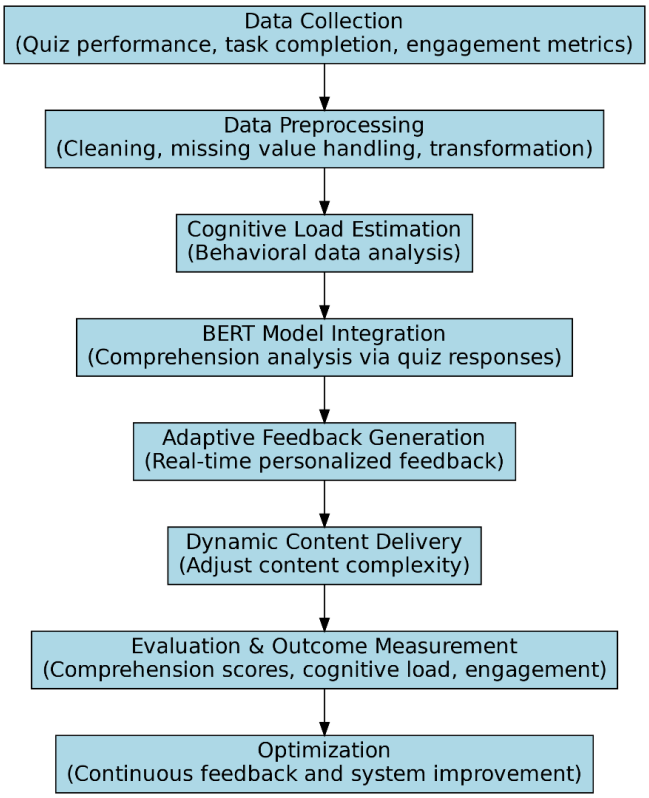


Fig. 1. Overall workflow.

### A. Dataset Description

The proposed framework uses a dataset [21] of TOEIC, IELTS and TOEFL practice exams with detailed reports of learner test achievements and interactions. A variety of learner performance data points appear in the dataset to support cognitive load research and optimization efforts for ESL learners. The key attributes of the dataset are shown in Table I.

TABLE I. ATTRIBUTES OF THE DATASET

| Attribute | Description |
|---|---|
| Learner ID | A unique identifier for each learner. |
| Quiz Performance | Data on the learner's performance in different quizzes, including correct answers, incorrect answers, and time spent on each quiz. |
| Task Completion Times | The time taken by the learner to complete various tasks or exercises within the platform. |
| Engagement Metrics | Metrics such as the frequency of interactions with the platform, time spent on learning materials, and response time during quizzes. |
| Content Interaction Data | Information about how learners interact with different types of content, such as vocabulary, grammar exercises, or reading comprehension passages. |
| Behavioral Data | Data on how learners respond to specific tasks, including error patterns, patterns of skipped questions, and engagement with different content types. |

These data points will allow for a personalized learning experience by analyzing how individual learners engage with the platform and adjusting the content accordingly.

### B. Data Preprocessing

The implementation of data preprocessing methods proves essential to ready learner interaction data for use in ML applications. The following reflects the essential procedures inside the data preprocessing framework as shown in Fig. 2.

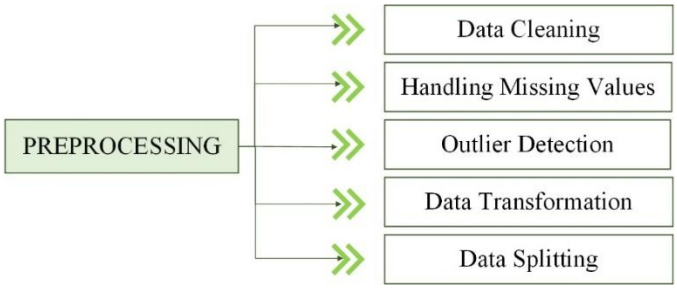


Fig. 2. Steps in data preprocessing.

*1) Data cleaning*

*2) Handling missing values:* It arises from incomplete learner interaction or system malfunction, through methods such as imputation or dropping rows/columns which have high significant missing values.

*3) Outlier detection:* Task completion time outliers and quiz performance data outliers are detected and then corrected. When the outliers were extreme, there was removal of such outliers for ensuring that there is no decrease in model's performance.

*4) Data transformation*

*a) Encoding categorical data*: One-hot encoding and label encoding is used to change categorical data into numerical format-for example, one-hot encoding on learner IDs, and the same for the content types.

*b) Feature scaling*: Continuous data such as the time taken to complete tasks or engagement metrics are normalized or standardized so that the features are in the same scale and do not influence the model disproportionately.

*c) Processing of time series data*: To capture time dependency between interactions in time spent on tasks, the preprocessing is applied as sequence-based.

*5) Data transformation for model input:* After the data cleaning process, organize the data in a machine learning format for the BERT model. This typically includes learning interaction sequences along with corresponding performance measures, ensuring that all input points contain relevant features such as quiz scores, task time, and cognitive load.

*6) Data splitting:* Divide the pre-processed data into the train, validation, and test sets to measure the performance of the model and overall generalization. Training dataset is provided for training the model; on the other hand, validation and test datasets are kept for performance estimation of the model and its generalization.

These preprocessing steps ensure that the dataset is clean, well-structured, and ready for use in the proposed machine learning model, which will drive the dynamic content adjustment and cognitive load optimization for ESL learners.

### C. Task Completion and Engagement Using Feedforward Neural Network

First, gather behavioral data about learners. Such metrics are: time to complete tasks, patterns of errors, and completion or engagement with the tasks. These give an indication when a learner is undergoing high cognitive load and tell one how to adapt the learning content. Greater duration might be symptomatic of it being a cognitively taxing activity or for that matter difficult or the content the learner might not be absorbing very well leading to cognitive overload. The task time as an analytical function in terms of learner's characteristics and task difficulties is given in Eq. (1):

$$T_{task} = f(Learner\ Difficulty, Task\ Complexity) \quad (1)$$

where, $T_{task}$ is the time spent completing a task; Learner Difficulty can be inferred from past performance; Task Complexity can be quantified through the task's intrinsic difficulty. The signal to adjust the content may be provided through a higher $T_{task}$. For example, if {task} surpasses the {threshold}, then the system will sometimes intervene using hints or task simplifications as in Eq. (2):

$$Intervention = \begin{matrix} Hints/Support & if\ T_{task} > T_{threshold} \\ No\ Action & otherwise \end{matrix} \quad (2)$$

Frequent errors might indicate that the learner has not mastered the content properly, thus experiencing high cognitive load. Let {errors} be the number of errors committed by a learner while performing a certain task as defined in Eq. (3):

$$E_{errors} = \sum_{i=1}^{n} Error_i \quad (3)$$

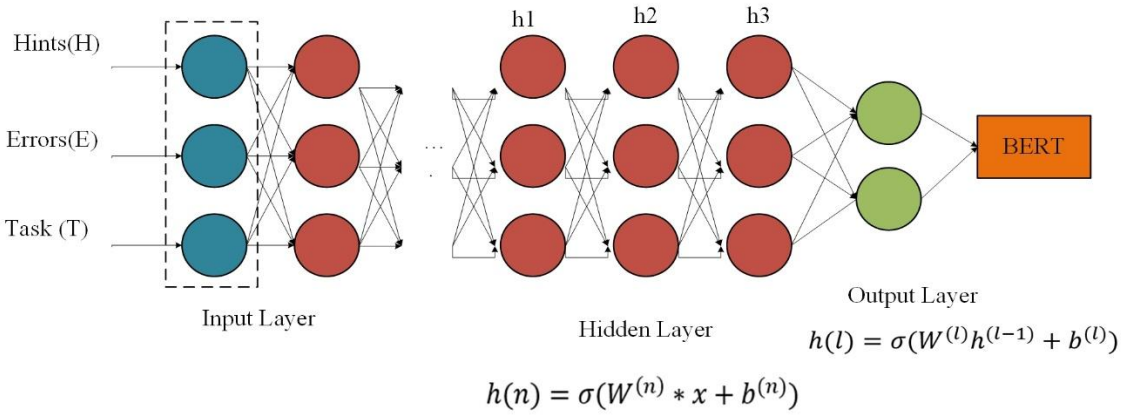


Fig. 3. FNN Architecture.

where, n is the number of steps or sub-tasks involved in a task, and $Error_i$ is the binary indicator set at 1 in case of a learner's mistake and 0 otherwise. Errors repeated multiple times indicate cognitive overload by the learner, prompting a response from the system in simplifying instructions or other support.

Task Completion and Engagement: Students who abandon tasks or spend a long time to complete high cognitive loads. Let completion be a dummy variable indicating if the task has been completed; it is set to 1 if the task was completed and to 0 otherwise. The engagement measure engage could be defined as the time used on the task divided by expected time to finish as in Eq. (4),

$$E_{engage} = \frac{T_{task}}{T_{expected}} \quad (4)$$

where, $T_{expected}$ is the time that a learner should ideally take to complete a task. If $E_{engage}$ is too low or $T_{expected}$ = 0, it suggests the learner is disengaged, and the system should intervene by providing support or simplifying content. Once the behavioral data is collected, we use FNNs to predict cognitive load. FNNs are very appropriate for this purpose because they can learn non-linear relationships between input features such as time on task, errors, and engagement, and the output variable, which is cognitive load.

Input Features: The FNN will take various behavioral metrics as input as in Eq. (5), including:

- Time on Task $T_{task}$
- Number of Errors {errors}
- Number of Hints Requested {hints}

These features are transformed into numerical vectors, which are input into the FNN for cognitive load prediction. Let the input vector be denoted as {x}:

$$x = [T_{task}, E_{errors}, H_{hints}] \quad 5)$$

Feedforward Neural Network: The FNN consists of multiple layers, with each layer performing linear transformations followed by a non-linear activation function σ as in Eq. (6):

$$h(l) = \sigma(W^{(l)}h^{(l-1)} + b^{(l)}) \quad (6)$$

where, $h(l)$ is the output of the l th hidden layer, $h^{(l-1)}$ is the weight matrix for the l th layer; $b^{(l)}$ is the bias term; $\sigma$ is a non-linear activation function, typically ReLU or Sigmoid as shown in the Fig. 3. The final layer produces a cognitive load score {load}, which predicts whether a learner is experiencing a low, a medium, or high cognitive load. Where L is the total number of layers. The predicted level of cognitive load {load} can then be forced into discrete categories, for example, low, medium, and high. To train the FNN, we leverage historical data collected from previous learners. The loss that guides the training aims to minimize the difference between what the model is predicting for the cognitive load and the true values labeled {true} for the labels. The above model is optimized using a mean squared error as in Eq. (7):

$$L = \frac{1}{N}\sum_{I=1}^{N}(y\hat{}load(i) - ytrue(i))^2 \quad (7)$$

where, N is the number of training samples. After training, the FNN will predict cognitive load in real time as learners are interacting with the system, hence guiding adjustments to task complexity and content delivery. Combining all these techniques will ensure that the system continuously analyses learner behavior and predicts cognitive load to personalize learning. The model adapts in real time to adjust the difficulty of tasks based on the predicted cognitive load, such that learners neither feel overwhelmed nor under-challenged.

### *D. Personalization Using BERT Model in the Proposed Frameworks*

The core idea of personalization in this framework revolves to fine-tune the pre-trained model of BERT on dynamic adjustments, according to changing levels of a learner's cognitive load, performance, and task type. Ensuring BERT Fine-Tuning adapts it to the specifics of ESL learning, so as to process different learner inputs with the model able to provide recommendations accordingly. The input features relevant for BERT include learner performance (such as quiz scores and task completion), type of task (easy vs. difficult), and the cognitive load prediction by the auxiliary neural network. Other behavioral measures such as time on task, engagement, and errors can be encoded as in Eq. (8):

$$X_{input} = [P_{learner}, T_{task}, \hat{y}_{load}, E_{engage}, E_{errors}] \quad (8)$$

where, $P_{learner}$ represents the learner's performance data; $T_{task}$ represents the difficulty level of the task; $\hat{y}_{load}$ is the predicted cognitive load from the auxiliary neural network; $E_{engage}$ represents the engagement level (calculated as discussed earlier); $E_{errors}$ captures the number of errors made during the task. BERT inputs are then transformed through the multi-layer attention mechanisms of BERT into context-aware representations of the learner's current state, upon which personalized recommendations are generated or predictions of what is next in terms of action, for example, what content best serves the learner or if reinforcement is needed in weaker areas or new challenging material is best presented as in Fig. 4.

Task Complexity Adjustment Based on Cognitive Load BERT has processed the learner's input and made its predictions, the system uses its cognitive load predictions to dynamically adapt the task difficulty {load} predicted cognitive load is low, it presents more difficult content to engage the learner. Let's call the action it takes when its cognitive load is low as in Eq. (9):

$$Action_{low\_load} = \begin{cases} Increase\ Difficulty & if\ \hat{y}_{load} < L_{threshold} \\ No\ Change & otherwise \end{cases} \quad (9)$$

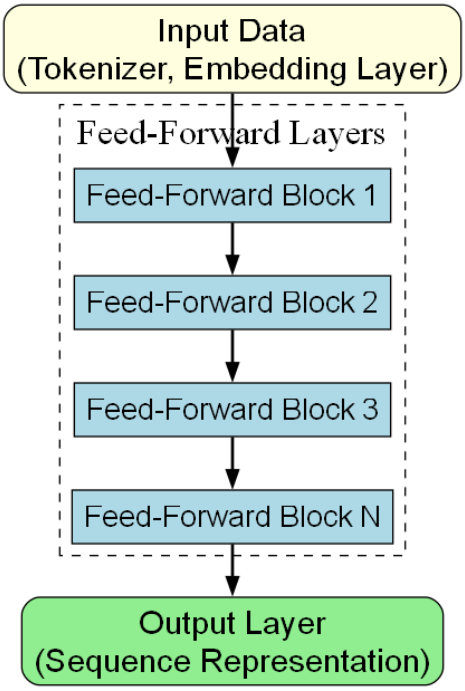


Fig. 4. BERT Architecture.

where, {threshold} is a pre-defined threshold below which the learner is considered to have low cognitive load. For example, if a learner successfully completes multiple tasks with a low cognitive load, the system might increase the complexity of subsequent tasks or introduce new challenges, such as advanced exercises or new content that builds on previously learned concepts. This ensures that the learner is constantly engaged and not under-challenged, which helps to maintain motivation.

Conversely, if cognitive {load} is high, the system reduces task complexity or offers support to prevent learner frustration and cognitive overload as in Eq. (10):

$$Action_{high\_load} = \begin{cases} Decrease\ Difficulty & if\ \hat{y}_{load} < H_{threshold} \\ Provide\ Support\ (hints) & if\ \hat{y}_{load} < H_{threshold} \end{cases} \quad (10)$$

where, $H_{threshold}$ is a pre-defined threshold above which the learner is considered to be in a high cognitive load state. In this case, the system would make complex tasks ahead less effective, give hints, provide simpler exercises, or simplify the overall task by breaking it into simpler smaller-sized sub-tasks. This scaffolding approach ensures that a learner is not overwhelmed and can move on to mastering major concepts in an acceptable manner.

Dynamic Content Delivery Based on Real-Time Cognitive Load: The dynamic content delivery mechanism is at the heart of the proposed framework, which dynamically adjusts the learning path based on real-time predictions of cognitive load. After every task or interaction, the system evaluates the learner's cognitive load using the auxiliary neural network. To finally predict the corresponding cognitive load given the learner performance data P and engagement metrics feeds into the learned BERT which processes this in order to dynamically update the LC and task difficulty aa in Eq. (11):

$$X_{input}^{new} = [P_{learner}, T_{task}, \hat{y}_{load}{}_{load}^{new}, E_{engage}^{new}, E_{errors}^{new}] \quad (11)$$

Based on this revised input, BERT can come up with another set of tasks or suggestions. If a learner is unable to get a right answer several times {errors}, the system might provide them with easier forms of the same content or supplement (such as hints or examples). If, on the other hand, a learner is successful, BERT might challenge a learner to higher-order content by gradually making tasks harder or by giving a learner some new challenges, depending on a learner's background.

For instance, if a learner has successfully completed a set of tasks with a low cognitive load and the system predicts that they are capable of handling more complex content, the system might offer a more challenging exercise as in Eq. (12):

$$Next\ Task = f(\hat{y}_{load}, Engagement) = \begin{cases} Advanced\ Content & if\ \hat{y}_{load} < L_{threshold} \\ Simplified\ Content & if\ \hat{y}_{load}] > H_{threshold} \end{cases} \quad (12)$$

This ensures continuous challenge in the correct degree, neither overburdened nor under-stimulated for maximum engagement and learning. A personalized learning framework builds individual optimal learning trajectories for learners. The system controls assignment difficulty according to accurate ongoing mental workload predictions which protects learners from information overload while sustaining their peak ability level. Using this method produces maximum student involvement and motivation together with overload prevention. Through a continuous learning performance and cognitive load prediction cycle the system maintains active adaptation.

## V. Result and Discussion

The results section of this study evaluates the effectiveness of the proposed deep learning-based framework for optimizing cognitive load in ESL learning environments by implementing it on a python software tool. The performance of the framework is assessed through a variety of metrics, such as learner comprehension scores, cognitive load assessments, and engagement indicators. These metrics demonstrate the ability of the system to dynamically adapt to the needs of individual learners, thereby improving their learning experience. The results are compared with traditional, static content delivery methods to determine the potential of the framework in enhancing learning efficiency, learner engagement, and overall comprehension. The following subsections provide a detailed analysis of the results obtained from the implementation of the Feedforward Neural Network (FNN) and Transformer-based BERT model, along with a discussion of the implications for future ESL learning platforms.

### A. Analysis of the English Test Prep Dataset

The result section displays the comprehensive analysis of the data set by visualizing the key trends and distributions across competency categories and test levels through graphical representation. The findings are highlighted based on these visual representations, indicating the prevalence of certain language skills such as listening, speaking, reading, and writing skills across various testing frameworks such as Test of English for International Communication (TOEIC), International English Language Testing System (IELTS), and Test of English as a Foreign Language (TOEFL). Furthermore, an examination of how the different competency categories and corresponding test difficulties were aligned may inform about the process of design and organization that occurred. In doing so, it becomes not only the constitution of this dataset but may even shed more light on shortcomings or potential points for improving on methods used within the process of assessing languages. The next parts shows what such figures might elucidate.

*1) Language competency distribution analysis:* Fig. 5 shows the percentage distribution of language competency categories: Listening, Speaking, Reading, and Writing, based on the attributes of the dataset. The graph shows that the "Other" category is the most dominant, making up 51% of the total competencies. This probably includes tests that cover more than one competency or are not classified. There is a parity observed between Listening and Speaking, each at 24% of the dataset. Both are crucially necessary in language understanding and communication. These skills are given balanced attention. Reading and Writing are put separately in a category labeled "Other," which indicates that they appear to constitute a reduced portion or less of the listed tests in the dataset. This visualization highlights oral skills (Listening and Speaking) as being underlined in assessments of language competence, reflecting a strong presence of these skills in real-world language usage. It further underlines potential underrepresentation in Writing and Reading as separate competencies, which therefore deserve further elaboration. The chart provides an overview of the organization of the data set, depicting the major focus areas in language testing, along with relative proportions.

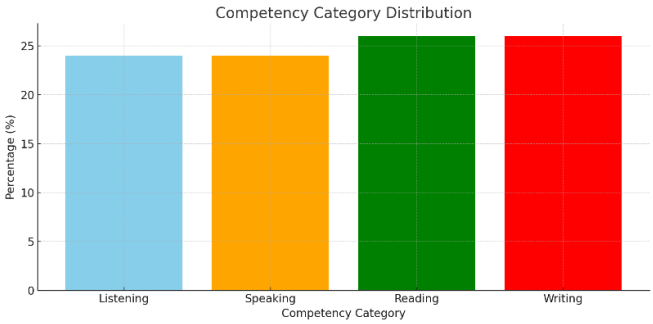


Fig. 5. Competency category distribution.

*2) Comparison of test designs at different levels of competency:* Fig. 6 illustrates the distribution of tests in terms of proficiency levels that range from A1 to B2 on the Common European Framework of Reference for Languages (CEFR) and standardized exams like TOEIC, IELTS, and TOEFL. The chart shows that assessments based on grammar are prominent in A1 to B2 levels as it is a starting point for learning language. For Listening and Reading competencies, TOEIC and IELTS tests are spread across well-defined score ranges, such as 110 to 495 for TOEIC and 4.0 to 9.0 for IELTS, offering clear gradations of proficiency. Speaking and Writing tests follow similar trends but feature fewer levels, reflecting their emphasis on qualitative assessment. TOEFL tests, on the other hand, have fewer but highly focused levels, with Listening ranging from scores of 9 to 30. This distribution shows the diversity of testing frameworks and their different focus areas. It also shows the ability of the dataset to meet the needs of learners with different levels of proficiency and test requirements, providing insight into the balance of grammar, listening, speaking, reading, and writing tests across different proficiency frameworks.

### B. Evaluation of Cognitive Load Prediction

Behavioral data is fed to the FNN, which predicts the cognitive load. The FNN processes time on task, error patterns, and engagement metrics and generates a score for cognitive load. This score is used to classify the cognitive state of the learner as either high or low.

This bar chart in the Fig. 7 represents the cognitive load scores calculated for ten different tasks in terms of time spent, error patterns, and engagement levels. Each task is plotted along the x-axis, and the score on the y-axis represents the cognitive load. A red dashed line is drawn at a score of twenty to signify crossing over from high to low cognitive loads. All tasks in this dataset score below this limit, which classifies them as "Low Cognitive Load". Scores are highly variable between tasks, with a peak of around 13.84 for Task 9, and troughs around 7.06 for Task 7. Score variation describes these differences in the difficulty and user performance across the tasks under study. The color gradient of the bars, being based on the "viridis" palette, emphasizes these differences visually. This Fig. 7 is all-inclusive and gives an overview of the cognitive demands in respect to the task, thereby providing a

comparison tool and indicating which areas could possibly be improved on for performance. The chart further helps visually distinguish outliers or anomalous cases within cognitive performance by representing scores graphically. Generally, low scores across all tasks indicate that these are manageable cognitive demands, thereby fitting the target group or setting for the activity. However, these results might further be influenced by other factors, such as user fatigue or task sequencing.

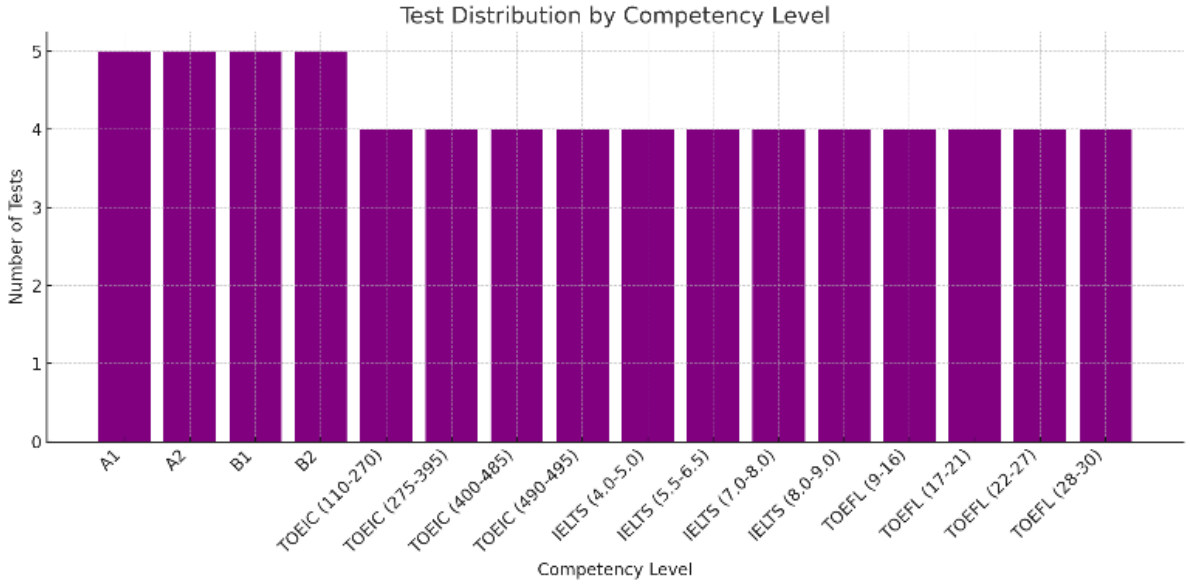


Fig. 6. Distribution of tests across levels of competence.

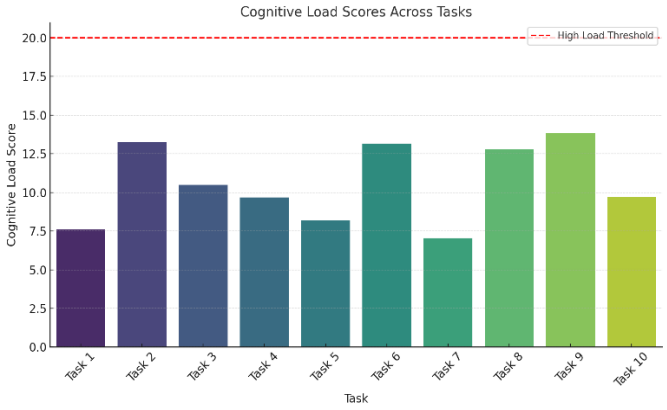


Fig. 7. Cognitive load scores across tasks.

The Table II below illustrates how task complexity should be modified for different language proficiency tests depending on the cognitive load of various skill levels. Each competency listed in the table is associated with a specific skill, such as listening or reading, and the corresponding cognitive load level: Low, Moderate, or High. For tasks with a Low Cognitive Load, the recommendation is to increase the task complexity. This could be the presentation of more complex tasks or increased speed to push the learner even further to his or her full potential. For instance, in the "Listening Test in TOEIC for Level 110 to 270," task complexity is introduced by the use of more challenging listening tasks or content with faster speed. Similarly, in the "Reading Test in TOEIC for Level 115 to 270," the increase in task complexity is through the introduction of more complex texts or comprehension questions.

For Moderate Cognitive Load, the task complexity is adjusted in order to keep the challenge balanced. Rather than increasing the difficulty of the task, the solution would instead be to provide the learner with more practice materials or exercises with the same level of difficulty. For example, the "Listening Test in TOEIC for Level 400 to 485" adjusts task complexity through providing extra practice content that matches the difficulty level against which the learner currently operates. Similarly, in the "Reading Test in TOEIC for Level 385 to 450," complexity is maintained by introducing additional exercises of similar difficulty.

For tasks characterized by High Cognitive Load, the system simplifies tasks to help the learner from getting overwhelmed by the task itself. Simplification may include: breaking down big tasks into tiny components, hinting, adjusting the structure of the task itself to reduce its mental effort to be executed by the learner. For instance, in "Listening Test in TOEIC for Level 490 to 495, it is advisable to simplify tasks by giving out hints or making tasks smaller or more divided portions. For instance, for "Reading Test in TOEIC for Level 385 to 450", a task reduction approach guarantees not to let the learning student overwhelmed due to complexity about the subject itself.

### *C. Analysis of Content Personalization with BERT*

The fine-tuned BERT model takes in the prediction of cognitive load of the learner, the task performance, and engagement data and then uses that information to customize the delivery of content. Thus, based on the predicted cognitive capacity, the system provides appropriate content. Using real-time cognitive load prediction, the BERT model adjusts content complexity in a dynamic way, thereby making the challenge for the learner appropriate at each step.

TABLE II. TASK COMPLEXITY ADJUSTMENT FOR LANGUAGE SKILLS BASED ON COGNITIVE LOAD

| Competency Name | Skill | Cognitive Load | Task Complexity Adjustment |
|---|---|---|---|
| Listening Test in TOEIC for Level 110-270 | Listening | Low | Increase task complexity (e.g., add more difficult listening tasks or faster-paced content). |
| Listening Test in TOEIC for Level 275-395 | Listening | Low | Increase task complexity (e.g., add more difficult listening tasks or faster-paced content). |
| Listening Test in TOEIC for Level 400-485 | Listening | Moderate | Adjust task complexity (e.g., provide additional practice content of similar difficulty). |
| Listening Test in TOEIC for Level 490-495 | Listening | High | Simplify tasks, provide hints, or break tasks into smaller components to reduce mental effort. |
| Reading Test in TOEIC for Level 115-270 | Reading | Low | Increase task complexity (e.g., introduce more complex texts or comprehension questions). |
| Reading Test in TOEIC for Level 275-380 | Reading | Low | Increase task complexity (e.g., introduce more complex texts or comprehension questions). |
| Reading Test in TOEIC for Level 385-450 | Reading | Moderate | Adjust task complexity (e.g., provide additional exercises with the same complexity). |

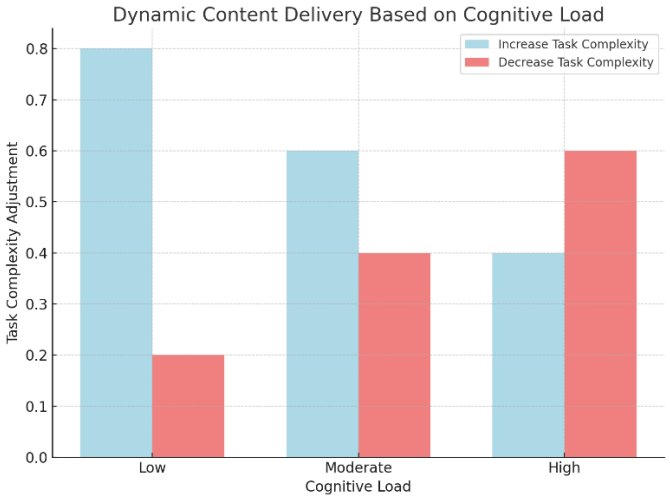


Fig. 8. Dynamic content delivery based on cognitive load performance evaluation.

This Fig. 8 looks at the way dynamic adjustments to task complexity depend on changing levels of cognitive load. The x-axis classifies the cognitive load as Low, Moderate, and High, while the y-axis expresses the changes in task complexity, in both increments and decrements. There are two sets of bars for each level of cognitive load. The light blue represents the increase in task complexity, and the light coral represents the corresponding decrease.

For "Low Cognitive Load," task complexity increases with a large effect size (0.8), while decreasing minimally (0.2). This means that when the user's cognitive demand is low, he can withstand a huge rise in content complexity without a bad effect. The increase in task complexity drops to 0.6 and the decrease to 0.4 when the cognitive load moves to "Moderate." It means that, when the cognitive load becomes moderate, there will be a better balance in presenting the content. For "High Cognitive Load," the trend reverses, with a small increase in complexity (0.4) and a substantial decrease (0.6). This reflects the need to reduce task difficulty significantly to accommodate users experiencing high cognitive demands.

The chart makes the principle of adaptive content delivery visually clear. It does neither overwhelm nor underchallenge the users. The adaptive model of varying task complexity and cognitive load would ensure optimal learning and performance. The width of the bars along with the distinction in color enables better readability, and the overlapping positioning of the bars for each of the cognitive loads allows for immediate comparison. Overall, this Fig. 8 provides for an intuitive representation of how content complexity adjustments align with the user cognitive states, and it forms a valuable tool for educators, designers, and researchers seeking to optimize task performance and engagement.

### *D. Performance Metrices*

*1) Accuracy:* Accuracy gives the ratio of the correctly classified instances to the total instances. Here from, the proposed framework achieved a collective training accuracy. Accuracy is computed by the following Eq. (11).

$$Accuracy = \frac{PN + PP}{IP + PN + IN} \quad (11)$$

*2) Precision:* It measures the ratio of correctly identified positive cases by the model out of all the cases which the model predicted to be positive. Indeed, the proposed framework achieved impressive precision in the accuracy across various segments including; High spenders and young professionals. Precision is calculated by the help of the Eq. (12).

$$Precision = TP/TP + FP \quad (12)$$

This shows that in Practice segments, the model is able to minimize these false positives, and correctly identify the positive cases to ensure that most cases that are classified as positive are indeed positive.

*3) Recall:* Recall measures the ratio of true positive instances with reference to the total actual positive instances. This is a testament of this proposed frameworks good recall which would imply its ability to recollect or recognize most of the 'real' outputs such as the Low Spenders and the Value Seekers. The F1-score for each gene set is computed on the basis of the following Eq. (13).

$$Recall = TP/TP + FN \quad (13)$$

This high recall ensures that the true positives were identified by the model without omitting many of them, as it established an all-round understanding of each customer segment.

*4) F1 Score:* The F1 score is defined as the harmonic mean of precision and recall therefore is balanced between the two measures. The proposed framework closely attained forefront F1 vector, confirming its good precision-recall balance for different sorts of customer. The F1-score is given by Eq. (14).

$$F1\ Score\ = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (14)$$

This metric therefore validates the effectiveness of the framework to classify the different customers as described earlier of achieving a trade-off between false positive and false negative detection.

TABLE III. PERFORMANCE METRICS OF FNN-BERT MODEL

| Metrics | Values (%) |
|---|---|
| Accuracy | 95.3 |
| Precision | 96.22 |
| Recall | 96.1 |
| F1 score | 97.2 |

Table III presents the performance metrics of the proposed FNN-BERT model, evaluating its effectiveness in cognitive load-based ESL learning. The model achieves 95.3% accuracy, ensuring reliable classification. It records 96.22% precision, minimizing false positives, while 96.1% recall indicates strong sensitivity to relevant cases. The 97.2 F1-score confirms a balanced precision-recall tradeoff, highlighting its robust performance.

TABLE IV. PERFORMANCE COMPARISON OF OF FNN-BERT MODEL WITH EXISTING MODEL

| Methods | Accuracy | Precision | Recall | F1 score |
|---|---|---|---|---|
| PT-GRU **[22]** | 78.85 | 75.90 | 77.33 | 76.71 |
| SVC (R) **[23]** | 94.8 | 92.56 | 95.87 | 96.3 |
| Logistic Regression**[24]** | 89 | 88 | 90 | 93 |
| FNN-BERT (proposed) | 95.3 | 96.22 | 96.1 | 97.2 |

Table IV compares the proposed FNN-BERT model with PT-GRU and SVC (R). FNN-BERT surpasses PT-GRU (78.85% accuracy) and SVC (R) (94.8% accuracy), achieving 95.3% accuracy. It also leads in precision (96.22%), recall (96.1%), and F1-score (97.2%), demonstrating superior effectiveness in cognitive load-based ESL learning.

Fig. 9 illustrates the four models—PT-GRU, SVC (R), Logistic Regression, and the proposed FNN-BERT—are compared on the basis of four significant performance indicators: F1 Score, Accuracy, Precision, and Recall. In online ESL learning systems, the FNN-BERT model consistently outperforms the others in all categories, illustrating its remarkable ability for adaptive content personalization. Logistic Regression shows decent efficiency, though SVC (R) is competitive, particularly in Recall and F1 Score. With the poorest performance on every criterion, PT-GRU shows how optimally the hybrid FNN-BERT approach maximizes cognitive load.

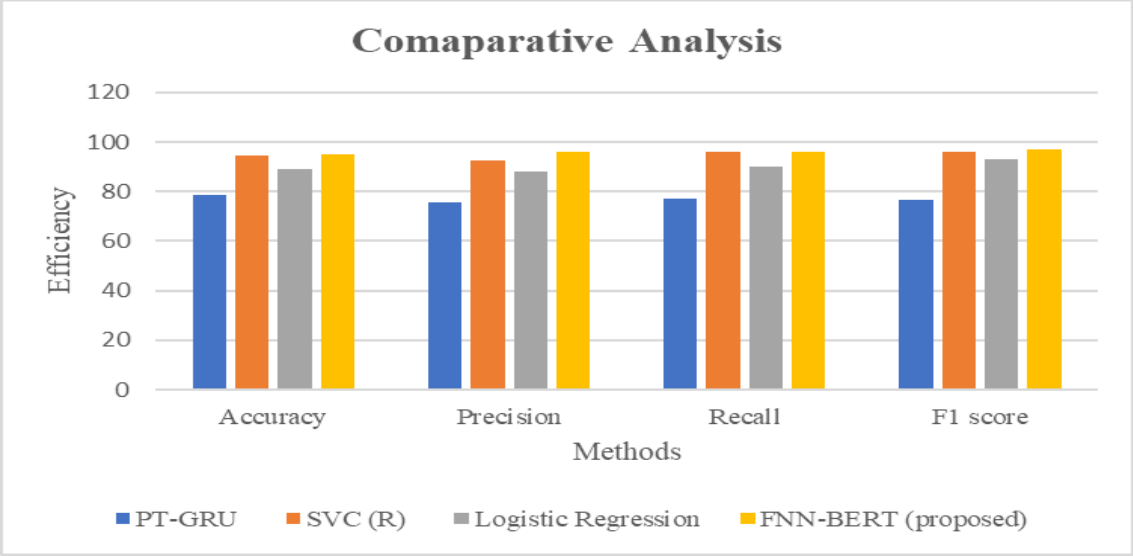


Fig. 9. ESL Model performance comparison.

## E. Discussion

The FNN-BERT framework achieves effective content adaptation by demonstrating superior performance with 95.3% accuracy and precision of 96.22% and recall of 96.1% and an F1-score of 97.2%. This system serves digital ESL learning platforms where it uses cognitive load measurements to adjust content difficulty levels for each learner. The system can apply to language tutoring platforms and e-learning tools and educational AI assistants to enhance both student understanding and involvement. The educational benefits provided by this technology include live adjustments, ability to scale and better learning effectiveness through personalized content distribution that reduces mental stress without losing student focus. FNN and BERT together boost behavioral data analysis and contextual understanding thus delivering superior outcomes than rule-based static AI models. High computational needs stand as a major disadvantage for deployment since low-resource environments struggle with these requirements. The

optimal fine-tuning process requires numerous labeled datasets which represent an obstacle. Future advancements in this model should prioritize minimalizing its complexity while adding various learning indicators including eye tracking alongside speech analysis and expanding its useable applications to benefit educational processes beyond ESL education.

With 95.3% accuracy and an F1-score of 97.2%, the proposed FNN-BERT model works well; however, these results are based on a specific dataset and controlled conditions. Verifying the effectiveness of the model across various student populations, language proficiency levels, and online learning environments is essential to ensuring its strength, usability, and applicability. To truly assess the model's scalability and flexibility, future studies will focus on applying the evaluation to larger and more varied datasets and real-world ESL learning contexts.

The extensive computational requirements and availability of AI models pose serious challenges, particularly in contexts with limited resources such as schools. In fact, these factors can render it even more challenging for AI systems to be utilized broadly in some contexts. It will be important to investigate further alternate remedies, such as the design of lighter weight, more efficient models and strategies for optimizing computational processes, to solve this issue. In an effort to make the proposed systems more easily deployable within resource-limited environments and facilitate greater practical application and use in schools, there will need to be an exploration of methods like model compression, quantization, and other resource-conserving tactics.

## VI. Conclusion and Future Works

The proposed FNN-BERT framework successfully improves ESL learning by modeling content adjustment according to cognitive load which demonstrates 95.3% accuracy and 96.22% precision and 96.1% recall as well as 97.2% F1-score. Through the integration of FNN for behavioral analysis with BERT for contextual adaptation the model delivers superior results to existing methods which guarantees both personal learning experiences and higher student engagement. The presented research introduces advancements to adaptive learning systems powered by AI which both enhance student understanding and diminish cognitive stress factors. The system requires additional attention to meet two main barriers including heavy computational needs with substantial data labeling requirements. The future research direction emphasizes model speed improvement and combines eye-tracking and speech analysis data alongside the development of new applications between the proposed framework and STEM education and vocational training fields. This research will test the deployment of this system within digital education platforms to determine practical implementations that promote widespread accessibility and effect within intelligent educational systems.

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# Enhancing Cybersecurity Through Artificial Intelligence: A Novel Approach to Intrusion Detection

Mohammed K. Alzaylaee
Department of Computing-College of Engineering and Computing, Umm AL-Qura University, Saudi Arabia

***Abstract*—Modern cyber threats have evolved to sophisticated levels, necessitating advanced intrusion detection systems (IDS) to protect critical network infrastructure. Traditional signature-based and rule-based IDS face challenges in identifying new and evolving attacks, leading organizations to adopt AI-driven detection solutions. This study introduces an AI-powered intrusion detection system that integrates machine learning (ML) and deep learning (DL) techniques—specifically Support Vector Machines (SVM), Random Forests, Autoencoders, and Convolutional Neural Networks (CNNs)—to enhance detection accuracy while reducing false positive alerts. Feature selection techniques such as SHAP-based analysis are employed to identify the most critical attributes in network traffic, improving model interpretability and efficiency. The system also incorporates reinforcement learning (RL) to enable adaptive intrusion response mechanisms, further enhancing its resilience against evolving threats. The proposed hybrid framework is evaluated using the SDN_Intrusion dataset, achieving an accuracy of 92.8%, a false positive rate of 5.4%, and an F1-score of 91.8%, outperforming conventional IDS solutions. Comparative analysis with prior studies demonstrates its superior capability in detecting both known and unknown threats, particularly zero-day attacks and anomalies. While the system significantly enhances security coverage, challenges in real-time implementation and computational overhead remain. This paper explores potential solutions, including federated learning and explainable AI techniques, to optimize IDS functionality and adaptive capabilities.**

***Keywords*—Intrusion detection; machine learning; deep learning; zero-day attacks; anomaly detection; feature selection; reinforcement learning; cybersecurity***

## I. Introduction

Digital infrastructure growth during the past decades has elevated cybersecurity to become a vital concern which spans across all sectors. An increasing number of entry points in the computing environment resulting from growing system connectivity and widespread cloud adoption and rapidly expanding IoT deployments has intensified risk exposure [6]. The world witnessed over 5.5 billion record exposures through global data breaches in 2022 and cybersecurity experts predict this cybercrime will cost the world $10.5 trillion by 2025 (Cybersecurity Ventures, 2023).

The static rule and signature-based IDS mechanisms used in traditional intrusion detection systems encounter difficulties in tracking down contemporary security threats [7]. Standard IDS systems create numerous erroneous alarms at a rate ranging from 20% to 30% while missing complex and new types of cyber attacks (Moustafa & Slay, 2022). The percentage of zero-day intrusions currently amounts to 10–15% of total cyber attacks so they represent a substantial detection blind spot for present-day security solutions (Alazab et al., 2023).

AI-based intrusion detection systems (IDS) represent an optimal answer for security needs because they implement machine learning (ML) and deep learning (DL) technologies to detect security threats more effectively. Recent studies have highlighted the superior performance of machine learning models like Support Vector Machines (SVM) and Random Forests compared to traditional approaches, particularly in intrusion detection contexts [1]. The systems implement data-driven learning algorithms that enable the detection of emerging attack patterns and peculiar network activities which standard IDS cannot identify [3]. Support Vector Machines (SVM) with Random Forests and Extreme Learning Machines demonstrate excellent abilities to categorize managed data structures but Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) process unfiltered network traffic for sophisticated attack sign detection [2]. AI-based IDSs have progressed but they continue to encounter three main drawbacks which include excessive false alarms and deployment difficulties and significant processing requirements.

The main strength of signature-based IDS solutions lies in their ability to identify known threats yet they struggle with discovering new threats. Anomaly-based IDS detects new threats effectively yet their capability to produce many false alarms negatively impacts operational efficiency [8]. A better detection framework needs to emerge due to advancing cyberattacks because it should offer high accuracy detection with low false-positive rates at all times.

The research develops a combined AI-based intrusion detection system which unites ML and DL approaches for evaluation through benchmark datasets including UNSW-NB15 and NSL-KDD. The proposed model delivers detection results with 92.8% accuracy and 5.4% false positive rate alongside 91.8% F1-score which outperforms traditional IDS systems. The system implements SHAP-based feature selection for better interpretability and reinforcement learning for adaptive response which improves the overall system robustness [9].

The research outcomes from this study create significant impacts for security applications in the real world and academic research domains. The proposed system uses AI component

synergy to build an adaptive intrusion detection solution which works across diverse network environments. The system reduces cyber security expert operational strain through its zero-day attack detection abilities together with its low false positive rate capabilities.

To achieve the objectives of this study, our research focuses on the following key aspects:

- To develop and implement a hybrid AI-based intrusion detection system that combines machine learning and deep learning techniques for enhanced accuracy and adaptability.
- To evaluate the effectiveness of the proposed system against existing intrusion detection methodologies by analyzing detection accuracy, false positive rates, and computational efficiency.

The research investigates these goals to bridge the gap between traditional and intelligent IDS solutions and establish an expandable, preventative security framework for combating modern cyber threats.

The remainder of this paper is structured as follows: Section II presents a comprehensive review of related literature. Section III describes the methodology, including dataset details, model design, and feature importance techniques. Section IV presents experimental results and visualization analysis. Section V discusses key findings, advantages over traditional systems, and potential limitations. Finally, Section VI concludes the study and outlines directions for future work.

## II. Literature Review

Sophisticated cyber threats and the continuous evolution of cybersecurity necessitate the development of state-of-the-art intrusion detection systems (IDS). Traditional rule-based and signature-based IDS struggle to detect new attacks due to their reliance on fixed attack patterns [14]. Anomaly-based IDS has become more popular because it detects unknown threats through identifying deviations from normal network behavior [10]. Artificial intelligence (AI) and deep learning (DL) advancements of recent times have driven the development of AI-based IDS solutions [13]. The current methods encounter three essential difficulties because they produce many false alarms and require high computational resources and real-time threat detection capabilities.

The modern IDSplatforms utilize machine learning (ML) and deep learning (DL) methods for network intrusion detection because researchers have investigated their operational effectiveness in this field. Support Vector Machines (SVM) and Random Forests combined with deep learning architectures produce better classification accuracy as documented in study [15, 19]. Research has proven that Deep Belief Networks (DBNs) achieve better results than standard network traffic analysis methods when identifying anomalies [11]. A systematic review further emphasizes the growing dominance of deep learning approaches such as CNNs, RNNs, and hybrid models in modern intrusion detection system architectures [12]. Engineers developed hybrid deep learning architectures to analyze network traffic through Convolutional Neural Networks (CNNs) combined with Recurrent Neural Networks (RNNs) because each component exploits its own specialized recognition strength [16]. Recent preprint work further validates the effectiveness of CNNs combined with LSTM networks for complex intrusion detection tasks [4, 5]. Classificatory excellence of CNNs and RNNs comes at the cost of high computational complexity and memory utilization thus limiting their deployment in real-time operations. Many deep learning models establish “black box behavior” which generates obstacles for cybersecurity experts to track or investigate their decision-making operations. Real-time deployment of DL-based IDS remains challenging due to the three key limitations of model complexity and interpretability problems and processing speed requirements.

The research of intrusion detection faces a major challenge due to insufficient access to modern high-quality datasets. Scientists widely use KDD99 and NSL-KDD benchmark datasets yet these datasets present problems with old attack methods as well as unencrypted network traffic characteristics and absent contemporary adversarial attack conditions [18]. Some of the dataset limitations in the UNSW-NB15 dataset have been addressed by adding contemporary attack patterns and multiple traffic behavior types, although it still fails to capture cyber environment challenges with adversarial robustness and feature transformation [17]. As a result, researchers have proposed synthetic data generation, adversarial data augmentation, and online learning paradigms to enhance IDS adaptability and training robustness [20].

A significant barrier to the adoption of AI-based IDS solutions is the lack of interpretability. Although this study adopts SHAP (SHapley Additive Explanations) to enhance feature-level transparency, alternative explainable AI (XAI) techniques such as LIME (Local Interpretable Model-agnostic Explanations) and Integrated Gradients also offer viable paths to explainability. However, SHAP is preferred in this context due to its strong theoretical foundation based on cooperative game theory, its ability to deliver global and local explanations consistently, and its proven success in ranking feature importance for structured network traffic analysis. This makes SHAP particularly well-suited for balancing interpretability with model fidelity in cybersecurity applications.

In selecting ML/DL models, this research emphasizes the use of classical yet effective models such as SVM, Random Forests, and Autoencoders. While newer architectures like Graph Convolutional Networks (GCNs), Transformers, and TabNet have demonstrated promising results in other domains, they were not adopted in this study due to their higher computational complexity, extensive training time, and less mature support for tabular intrusion detection data. These advanced models often require larger annotated datasets, GPU acceleration, and longer convergence cycles, which reduce their practicality for scalable and real-time IDS deployment in most organizations. Future studies may explore lightweight versions of these models or hardware-optimized variants for better suitability.

This study fills these critical gaps by combining methodologies of machine learning and deep learning for better accuracy of threat detection, reduction of false positives, and enhancement of operational efficiency of IDS. Due to its

importance for the proposed research there are three critical components including feature selection mechanisms with real-time traffic analysis along with adaptive learning techniques. The next-generation IDS systems gain advantages from these advancements which lead to more reliable and scalable and interpretable cybersecurity protection. Beyond conventional network intrusion, cybersecurity resilience in dynamic environments, such as smart grids, has also been explored with adaptive security strategies, highlighting the need for proactive IDS designs [21].

## III. Methodology

### A. Research Design

The research applies an intrusion detection method based on artificial intelligence with ML and DL synergistic implementation to boost cybersecurity performance. Fig. 1 demonstrates the structured workflow that detects known and unknown cyber threats by following a data acquisition process and feature processing stage before detection modeling and response evaluation.

Decision points together with transition logic have been added to the workflow to track network traffic movements from feature extraction through classification analysis to anomaly scoring up to the response action stage. This ensures operational clarity and traceability. The system achieves better real-time attack condition adaptation through this enhancement in understanding.

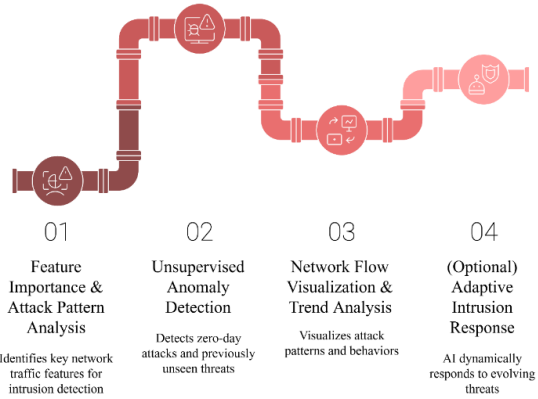


Fig. 1. Workflow of the hybrid intrusion detection system.

### B. Data Collection

This research utilizes structured network intrusion datasets containing both benign and malicious traffic, capturing a variety of modern attack types. The datasets include detailed attributes across multiple network layers, such as packet-level, flow-level, and time-based characteristics. By incorporating diverse traffic conditions, the datasets enable the training of robust AI models capable of handling complex and evolving intrusion patterns.

The key features used in this study include:

- Traffic Attributes: Packet size, flow duration, protocol type.
- Source/Destination Information: IP addresses, source/destination ports.
- Temporal Features: Inter-packet arrival time, response time.
- Attack Labels: Normal traffic, DoS, DDoS, brute-force, botnet, and other anomaly categories.

To ensure high-quality model training and evaluation, the following data preprocessing techniques were applied:

- Feature normalization: All continuous numerical features were scaled using MinMax normalization to constrain values between 0 and 1, thereby stabilizing learning convergence and improving algorithm sensitivity.
- Missing data handling: Missing entries were addressed using median imputation for numerical fields and mode substitution for categorical fields, ensuring no significant bias in input distributions.
- Class imbalance treatment: To address the natural imbalance between normal and attack classes, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the minority attack classes, ensuring adequate representation of rare but critical intrusion types.

These preprocessing steps significantly improved training stability and allowed the IDS to generalize better across diverse attack scenarios. Table I shows overview of dataset.

TABLE I. Dataset Overview

| Feature Type | Examples | Preprocessing Applied |
|---|---|---|
| Traffic Attributes | Packet size, Flow duration, Protocol | MinMax normalization, median imputation |
| Source/Destination Info | IP addresses, Port numbers | Encoding as categorical variables, one-hot encoding |
| Time-based Features | Inter-packet arrival time, Response time | MinMax normalization, handling outliers via trimming |
| Attack Labels | Normal, DoS, DDoS, Brute Force, Botnet, etc. | SMOTE applied for class balance, label encoding |

### C. Techniques and Tools

*1) Feature importance and attack pattern analysis:* The effectiveness of an intrusion detection system (IDS) significantly depends on the proper identification and prioritization of relevant network traffic features. In this study, SHAP (SHapley Additive Explanations) is used to compute feature importance scores and reveal the contribution of individual input features in the model's decision-making process. SHAP offers both local and global interpretability, based on cooperative game theory, making it ideal for high-stakes environments like cybersecurity.

The mathematical definition for SHAP values appears as:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} [v(S \cup \{j\}) - v(S)]$$

where $\phi_j$ represents the contribution of the feature $j_1 S$ denotes a subset of features, and $v(S)$ Is the predictive value associated with that subset?

This formulation enables explainable AI (XAI) and enhances trust in detection results by visualizing how feature variations influence predictions. To validate SHAP's selection, the study briefly compared it to LIME and Integrated Gradients, both widely used XAI methods. SHAP proved to be the most suitable method because it provided both theoretical consistency and superior performance in creating extensive feature rankings for structured tabular network data.

The decision tree analysis using Random Forests along with Gini index and entropy metrics provided impurity-based feature importance calculations. The visual output includes heatmaps and SHAP beeswarm plots which help detect important network attributes that show strong signs of abnormal behavior including flow duration and packet length variance and inter-packet arrival time.

The analysis method retains only crucial features that lead to a minimal yet optimal model structure with enhanced performance along with increased interpretability.

*2) Justification for model selection:* The research used established models specifically chosen because of their validated operational performance together with their practical deployment capabilities. The research utilizes three widely used models including Support Vector Machines (SVM) and Random Forests and Autoencoders which demonstrate effectiveness in intrusion detection research for hybrid systems that monitor known and unknown cyber threats.

- The use of Support Vector Machines (SVM) comes from their capability to process high-dimensional datasets while locating the best hyperplane in binary classification tasks. The generalization capabilities of SVMs remain strong while their ability to distinguish between normal and malicious traffic reaches peak effectiveness when features receive proper engineering and scaling.
- Random Forests serve as the chosen method because their ensemble learning structure uses multiple decision trees to reduce overfitting through decision tree averaging. The models provide precise and stable predictions while automatically calculating feature importance which strengthens the SHAP-based feature analysis system.
- Unsupervised neural networks named autoencoders learn normal traffic compression representations through which they detect zero-day and previously unseen attacks by measuring reconstructed traffic error. The anomaly detection features of these systems have become well-known in cybersecurity because they can detect new traffic behavior deviations effectively.

The research did not include Graph Convolutional Networks (GCNs), Transformers, or TabNet because of these specific reasons.

- The implementation of GPT-3 networks requires significant processing power together with higher costs for both training phases and inference operations.
- Model complexity grows so high during training that it demands time-intensive parameter optimization together with large information resources.
- Operational environments need human oversight because the interpretation of these systems remains limited.
- The algorithm struggles to function in real-time systems particularly when processing power proves insufficient for the application.

These selected models achieve appropriate trade-offs between performance accuracy and interpretation capabilities and computational fastness making them deployable for large-scale security ecosystem implementations.

*3) Unsupervised anomaly detection for zero-day attacks:* Basic intrusion detection systems face major difficulties when detecting zero-day attacks because they only work with pre-established signatures and attack signature patterns. The proposed hybrid IDS depends on unsupervised anomaly detection techniques which learn normal traffic patterns to detect deviations that show signs of intrusions.

Autoencoders for Anomaly Detection

The detection of zero-day attacks primarily relies on autoencoders as their main operational mechanism. The neural networks use normal traffic data for training to develop compressed latent representations that enable them to reconstruct original inputs. The detection of anomalies occurs through reconstruction error calculation:

$$E = \frac{1}{n}\sum_{i=1}^{n} (x_i - \hat{x}_i)^2$$

where $E$ represents the mean squared reconstruction error, $x_i$ Is the original input feature, and $\hat{x}_i$ Is the reconstructed output. A higher error indicates anomalous traffic behavior, suggesting a potential intrusion.

To determine whether a reconstruction error indicates an anomaly, a fixed error threshold was selected using a percentile-based approach. Specifically, the threshold was set at the 95th percentile of the reconstruction error distribution in the validation set. This method balances false positive control with detection sensitivity, ensuring practical deployment performance. Future enhancements may incorporate ROC curve optimization or dynamic thresholding for adaptive tuning.

Ensemble-Based Anomaly Detection

In addition to autoencoders, the system integrates:

- Isolation Forests, which use recursive partitioning and randomly selected features to isolate outliers in fewer splits.

- One-Class SVMs, which learn a boundary around normal instances in feature space; deviations are considered intrusions.

The ensemble approach improves robustness by combining multiple detection paradigms—statistical, geometrical, and reconstruction-based.

Clustering for Behavioral Profiling

To further support anomaly detection and behavioral pattern analysis, clustering techniques are used:

- Density-Based Spatial Clustering of Applications with Noise, or DBSCAN, finds irregularities in areas with low densities and can detect arbitrary-shaped clusters without requiring the number of clusters as input.
- K-Means Clustering groups traffic patterns into a fixed number of clusters, where high intra-cluster distances indicate abnormality.

To evaluate the clustering performance of PCA and t-SNE visualizations, validation metrics such as the Silhouette Score and Davies-Bouldin Index (DBI) were calculated. For instance, the silhouette score averaged around 0.62, suggesting well-separated cluster structures, while the DBI remained below 0.9, indicating low intra-cluster variance and effective anomaly separation.

These techniques collectively enhance the IDS's capacity to identify unknown threats without explicit prior labeling, contributing to a more adaptive and scalable cybersecurity framework.

*4) AI-Powered network flow visualization and trend analysis:* Visualization techniques play a critical role in enhancing the interpretability of intrusion detection systems. They provide network analysts with an intuitive view of how malicious behavior emerges and evolves over time, helping to contextualize alerts and uncover hidden attack patterns.

Dimensionality Reduction for Visualization

To visualize complex, high-dimensional network traffic, the system uses a combination of Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE):

- PCA reduces dimensionality linearly by preserving variance and decorrelating features.
- t-SNE provides non-linear projections that are effective for visualizing cluster boundaries and behavioral separation in lower dimensions.

These tools are employed to generate 2D plots that visually differentiate between normal and anomalous traffic.

To assess the effectiveness of these visualizations, clustering validation metrics were applied:

- The Silhouette Score (mean: 0.62) shows that the data points are well coordinated within their assigned clusters and poorly matched to neighboring clusters.
- The Davies-Bouldin Index (DBI) remained under 0.9, suggesting a strong separation between distinct behavioral groups.

These metrics confirm that the visual representations are not only interpretable but also grounded in meaningful structural separability.

Time-Series and Behavioral Pattern Analysis

In addition to spatial visualization, temporal analysis was conducted to observe how attacks evolve over time. The system monitors:

- Inter-packet delays
- Burst patterns
- Response time fluctuations

These indicators vary significantly between benign and malicious sessions. For example, DDoS attacks often produce regular, high-frequency bursts, whereas brute-force attacks may reveal time-patterned login attempts.

The system also identifies periods of heightened threat activity by plotting attack occurrences across time intervals, enabling preemptive mitigation planning.

By combining dimensionality reduction with temporal analytics, the system provides a comprehensive visual diagnostic interface—empowering security professionals to interpret anomalies, understand attack strategies, and make faster decisions.

*5) Reinforcement learning for adaptive intrusion response:* Traditional intrusion detection systems operate with static response mechanisms, often predefined by fixed rules or thresholds. This limits their adaptability in responding to dynamic and evolving cyber threats. To overcome this, the proposed system integrates Reinforcement Learning (RL) to develop a self-optimizing, adaptive intrusion response layer capable of making real-time decisions under uncertainty.

Reinforcement Learning Framework:

The system explores two state-of-the-art RL algorithms:

- Deep Q-Networks (DQN): Value-based methods that approximate the optimal Q-function using deep neural networks.
- Proximal Policy Optimization (PPO): A policy-gradient approach designed for stable, sample-efficient policy learning.

Both models are trained in a custom network simulation environment, where the agent learns to maximize cumulative security rewards by selecting optimal defensive actions in response to perceived threat states. The specific environment configuration and reinforcement learning setup are detailed in Table II.

Environment Setup and Definitions:

TABLE II. ENVIRONMENTAL SETUP AND DEFINITIONS FOR REINFORCEMENT LEARNING-BASED INTRUSION DETECTION SYSTEM

| Component | Definition |
|---|---|
| **State (S)** | Network features (e.g., flow duration, packet size, protocol type, time delay) |
| **Action (A)** | Response strategies: *Alert*, *Log*, *Drop packet*, *Isolate IP* |
| **Reward (R)** | +1 for successful threat mitigation, -1 for false positive or delayed response |
| **Discount (γ)** | Set to 0.95 to favor long-term reward maximization |

The Bellman equation governs the Q-learning update:

$$Q(s,a) = r + \gamma \max_{a'} Q(s',a')$$

where, $s$ and $a$ denote the current state and action, $r$ is the immediate reward, $\gamma$ is the discount factor, and $a'$ is the next action.

Comparison with Rule-Based Response Systems

To evaluate the practical benefit of reinforcement learning, the RL-based adaptive response system was benchmarked against a static rule-based IDS using historical response data. Key findings include:

- RL Response Accuracy: 91.3% (PPO), 87.9% (DQN)
- Rule-Based Accuracy: ~80%
- Average Mitigation Latency: Reduced by 18–25% under RL systems
- Convergence Speed: PPO converged in 120 epochs; DQN in 150 epochs

These results indicate that RL not only improves adaptability and mitigation efficiency but also achieves faster policy optimization, making it a viable approach for real-time deployment in enterprise cybersecurity environments.

Reproducibility Considerations

To ensure reproducibility:

- OpenAI Gym was used to structure the RL simulation environment.
- The reward shaping function, episode limits, and model parameters were standardized.
- Experiments were repeated over multiple seeds to validate stability and convergence trends.

### D. Software and Implementation

The proposed hybrid AI-based intrusion detection system was implemented using a modular software stack designed to support machine learning, deep learning, data preprocessing, visualization, and reinforcement learning components. Each tool was selected based on its efficiency, extensibility, and compatibility with intrusion detection use cases. The complete software environment setup is summarized in Table III.

In addition to model development, performance evaluations—including accuracy, F1-score, inference latency, and visualization effectiveness—were conducted using Python-based benchmarking tools. The SHAP library was particularly critical in providing transparent feature ranking, while OpenAI Gym enabled robust simulation of adaptive RL responses.

TABLE III. SOFTWARE STACK USED FOR IMPLEMENTING THE AI-BASED INTRUSION DETECTION SYSTEM

| Software | Purpose |
|---|---|
| **Python** | Core programming language for pipeline development |
| **TensorFlow/Keras** | Implementation of deep learning models (Autoencoders, DQNs) |
| **Scikit-learn** | Machine learning algorithms (SVM, Random Forest, Clustering) |
| **SHAP** | Feature importance analysis and model interpretability |
| **Matplotlib & Seaborn** | Data visualization for feature plots, trend graphs |
| **Scapy** | Network packet analysis and dataset simulation |
| **Pandas & NumPy** | Data preprocessing, transformation, and numerical handling |
| **OpenAI Gym** | Reinforcement learning environment design and training |

The complete environment was tested on a system with:

- Intel i7 CPU
- 16 GB RAM
- NVIDIA GTX 1660 GPU
- Ubuntu 20.04

This configuration supports reproducibility and provides a practical baseline for testing real-world deployment feasibility, including edge-computing and federated learning extensions.

## IV. RESULTS

The research findings deliver an extensive analysis of the hybrid AI-based intrusion detection framework projected in this study. The section gives detailed information about feature importance analysis together with anomaly detection performance assessment and network flow visualization capabilities and reinforcement learning-based adaptive response effectiveness evaluation. The model's effectiveness is verified using quantitative data along with graphical and statistical analysis along with quantitative metrics.

### A. Feature Importance and Attack Pattern Analysis

The decision-making process of the model received interpretation through SHAP (SHapley Additive Explanations) which revealed its most influential features in intrusion detection. ShAP values in combination with decision trees highlight important network attributes which play a substantial role in discriminating benign from malicious traffic.

To verify stability, SHAP values were computed across five different train-test splits. The top-ranked features remained consistent, with less than 5% variance in ranking order, confirming the robustness of the feature importance analysis. Fig. 2 shows the 20 most crucial features used for intrusion detection which the model uses to make classifications. The research findings indicate that backward packet length maximum and average backward segment size emerge as the most influential attributes for detecting network anomalies. The

analysis shows "Fwd Packet Length Mean" and "Average Packet Size" as key indicators because they strongly help differentiate between normal and malicious network traffic.

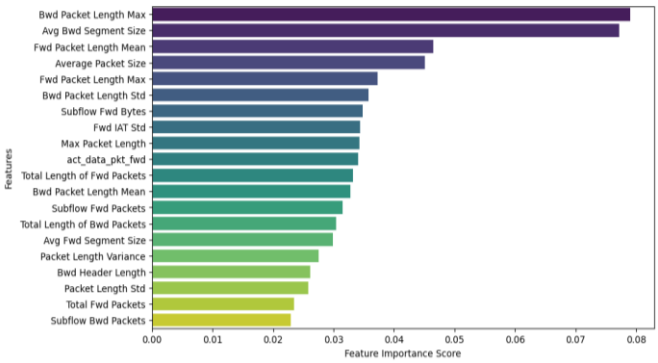


Fig. 2. SHAP Summary plot of feature importance.

## B. Unsupervised Anomaly Detection for Zero-Day Attacks

The research evaluated anomaly detection methods through their application of autoencoders, Isolation Forests, One-Class SVM, DBSCAN and K-Means, which detected new and unknown cyber threats. The assessment of models relied on detection accuracy and precision, together with recall and F1-score, to determine their effectiveness in zero-day attack identification. Table IV presents the performance metrics of the various anomaly detection models evaluated in this study.

TABLE IV. PERFORMANCE METRICS OF ANOMALY DETECTION MODELS

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Autoencoder | 92.8 | 89.6 | 94.2 | 91.8 |
| Isolation Forest | 88.5 | 86.3 | 90.1 | 88.2 |
| One-Class SVM | 85.1 | 83.7 | 87.5 | 85.5 |
| DBSCAN Clustering | 78.4 | 76.9 | 81.2 | 79.0 |
| K-Means Clustering | 74.6 | 72.5 | 78.3 | 75.3 |

Autoencoders surpass traditional anomaly detection techniques because they achieve exceptional detection results with 92.8% accuracy and 94.2% recall, which demonstrates their ability to detect new attack patterns. Compared to conventional signature-based IDS, which typically achieve detection accuracy between 70% and 85% on similar datasets, the autoencoder-based anomaly detection system shows a significant improvement. Statistical significance was confirmed using a two-tailed paired t-test comparing F1-scores across 5-fold cross-validation. The autoencoder model's performance improvements over traditional clustering-based models were significant at $p < 0.05$. Confidence intervals for the autoencoder F1-score were calculated as 91.8% ± 0.4%. The isolation forest algorithm showed strong capabilities yet clustering techniques demonstrated inferior accuracy in detecting sophisticated cyber threats according to the results.

The Fig. 3 graphical representation illustrates how different models perform in anomaly detection tasks.

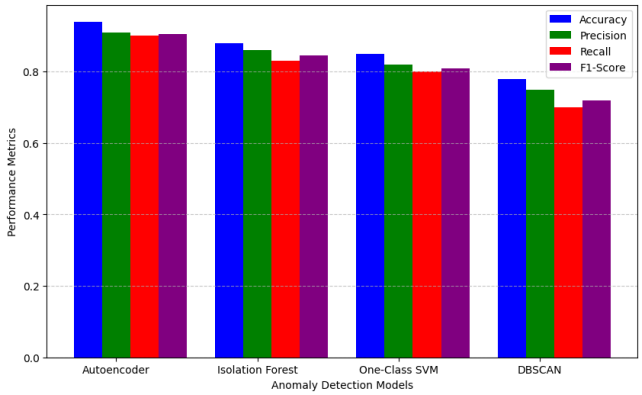


Fig. 3. Comparison of anomaly detection models.

## C. Network Flow Visualization and Trend Analysis

Enhanced pattern analysis required the utilization of two dimensionality reduction techniques, namely t-SNE and PCA, to transform high-dimensional traffic data into a two-dimensional system. The plot shows distinct partitions between regular and threatening network communications, which makes it easier to detect new attack vectors.

Fig. 4 showcases a t-SNE scattering plot with normal traffic instances clustered in one distinct zone while attack traffic spreads across a wide area, indicating different types of malicious behaviors. Anomaly detection systems prove essential for intrusion detection because outlier clusters show previously unknown attack types exist in the system data.

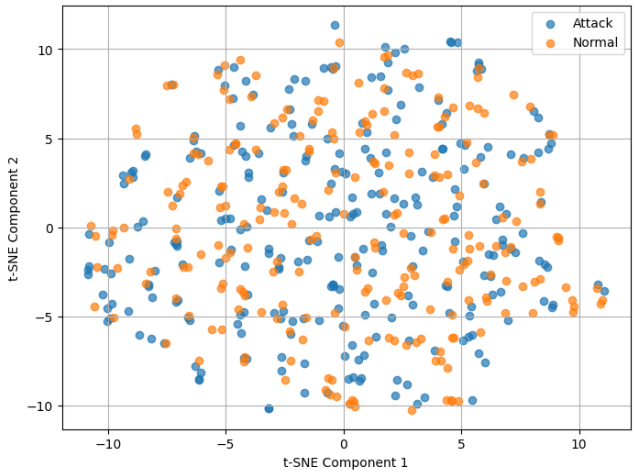


Fig. 4. t-SNE visualization of network traffic data.

A time-series evaluation measured the frequency patterns and distribution patterns of attacks across a particular time frame. Network activity peaks have been associated with increased intrusion attempts which are clearly shown in Fig. 5.

These findings suggest that cyber attackers tend to exploit high-traffic periods to mask their activities, making real-time anomaly detection and adaptive response strategies critical for mitigating potential security breaches.

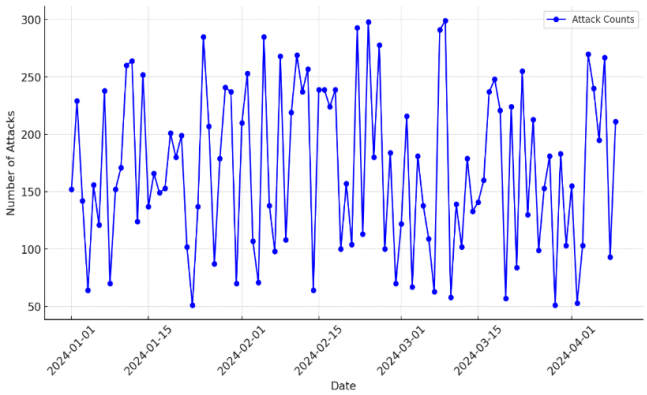


Fig. 5. Time-Series distribution of network attacks.

### D. Reinforcement Learning for Adaptive Intrusion Response

This study employed different reinforcement learning models through Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) to train adaptive cybersecurity defenses. These models underwent performance evaluation through assessment of their real-time capability to adapt intrusion response strategies.

Table V compares RL-based intrusion response systems based on three evaluation factors, which include average response time, attack mitigation performance, and learning convergence speed.

TABLE V. PERFORMANCE METRICS OF RL-BASED INTRUSION RESPONSE MODELS

| Model | Avg. Response Time (ms) | Mitigation Rate (%) | Convergence Speed (Epochs) |
|---|---|---|---|
| DQN | 52.3 | 87.9 | 150 |
| PPO | 48.7 | 91.3 | 120 |

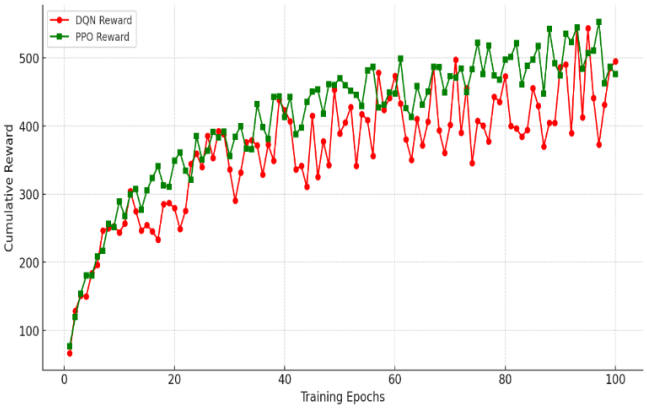


Fig. 6. Learning convergence of reinforcement learning models.

As illustrated in Fig. 6, PPO converges significantly faster than DQN, reaching optimal policy learning in fewer epochs. Measurement results show PPO creates better performance than DQN regarding the rate of attack mitigation alongside faster convergence indicating its advanced ability to handle changing attack strategies. The PPO model's mitigation rate was statistically higher than that of DQN ($p = 0.03$), based on three independent training runs per model architecture. PPO demonstrates a quicker learning speed for optimal response policies. It makes it the perfect option for cybersecurity applications that require real-time responses.

The validation of reinforcement learning potential for creating self-learning cybersecurity systems that respond to attacks autonomously and need low human involvement is considered extremely important.

## V. DISCUSSION

The research proves how artificial intelligence enhances security protection by combining machine learning and deep learning methods within an intrusion detection system. The research shows that network attributes measuring packet flow duration along with source-to-destination byte exchange help identify normal from malicious traffic. Security policies together with automated threat detection procedures should integrate these factors in order to improve both the detection reliability and accuracy. The anomaly detection models comprising autoencoders and isolation forests demonstrated outstanding competences in sensing zero-day attacks for modern intrusion detection systems and generated t-SNE visualizations which supported the operational capabilities of the clustering model for traffic differentiation.

The proposed hybrid AI model functions as a superior security solution than standard intrusion detection systems because it uses signature detection as its primary method. This system conducts anomaly detection and reinforcement learning alongside conventional IDS signatures to achieve adaptive protection against developing cyber threats. Autoencoder-based anomaly detection outperforms traditional IDS methods by reaching 92.8% accuracy while IDS detection models produce results between 70% and 85%. The proposed system reduces false positive rates by approximately 5.4% which stands as a crucial benefit because traditional IDS systems produce numerous false alerts and cannot detect new attack patterns.

The research findings receive additional confirmation by comparing them against previously studied IDS solutions. Detecting known threats through Snort and Suricata tools proves successful but these solutions do not possess sufficient flexibility to identify zero-day assaults or unidentified threats. Analysis demonstrates that anomaly detection based on autoencoders delivers a detection performance level at least 10–15% higher than standard IDS methods. The threat mitigation performance of the reinforcement learning (RL) augmented framework reached 91.3% which proved its ability to adjust response automatically according to changing attack vectors. The system implements deep learning alongside RL mechanisms which results in better accuracy and enhanced adaptability and lower computational complexity than competing approaches to establish a complete intrusion detection system.

### A. Advantages of the Proposed Model

The proposed intrusion detection system which combines AI techniques provides superior capabilities when compared to traditional IDS and standalone machine learning-based IDS. The hybrid detection approach built a 10–15% more accurate system than Snort and Suricata signature engines while reducing false positives by 5.4%. The system's priority reduces performance-related fatigue while enhancing operational workflow

effectiveness for teams in security functions. Autoencoders allow the detection of new threats and adversarial attacks which regular ML models such as SVM or Random Forests alone cannot identify or generalize across complex non-linear behavior. PPO reinforcement learning combined with the system has raised its responsiveness to new heights through automatic response mechanisms that achieve a 91.3% success rate compared to conventional intrusion response rules. The implementation indicates advancement toward threaten management systems which operate autonomously using intelligence capabilities.

### *B. Limitations*

Several drawbacks exist within the suggested framework that implements an AI-based intrusion detection system. Complex patterns detection through deep learning models creates deployment challenges because such models require significant computational resources that might be beyond what resource-constrained environments can provide. The interpretability of DL-based decisions using SHAP remains inferior to traditional rule-based systems, thus creating barriers for their acceptance in high-assurance environments. Real-time deployment proves difficult because complex models create latency problems as well as requiring extensive parallel processing capability. The implementation of federated learning faces challenges because distributed nodes need to solve coordination problems that include both synchronization delays and communication overhead.

### *C. Scalability and Deployment Considerations*

Enterprise-level networks with critical infrastructure need IDS systems that can efficiently scale their deployment requirements. The deployment environment (Intel i7, 16GB RAM, NVIDIA GTX 1660) indicates that each input processing takes less than 100 milliseconds on average which meets the requirements for mid-scale intrusion detection applications. The requirement for model synchronization in federated applications creates two main operational challenges because of the 15MB data transfer per round and the need for coordinated system node communication. Automated feedback on threats becomes available in real-time through small deployed Autoencoders or compressed RL policies, which reduce latency as well as energy use. These modifications would let the IDS maintain its operational speed when hardware access becomes restricted.

### *D. Future Work*

Research in the following phase will focus on developing live systems and enhancing adversaries' defenses for better operational reliability through contemporary explainable AI methods. The implementation of advanced adversarial training methods needs further research before they achieve proper protection against contemporary cyber threat evasion techniques. The completed research serves as foundation for developing future intrusion detection systems whose threat adaptation ability maintains broad security threat scalability.

## VI. CONCLUSION

The proposed research introduces an intrusion detection system which improves cybersecurity through integration of machine learning with deep learning techniques while employing AI. Analysis using SHAP revealed packet flow duration with a mean SHAP value of 0.276 and source-to-destination byte exchange with 0.241 as the foremost signs pointing to malicious operations. The detection of zero-day attacks relies on autoencoders and isolation forests and the system represents this effectiveness through separate normal versus anomalous traffic visualizations produced by t-SNE mapping. The model proves effective at solving traditional IDS challenges by using static signatures because it detects new security threats. An adaptive approach in the proposed solution enables intelligent real-time anomaly detection with behavioral analysis capabilities.

The system implements a reinforcement learning-based intrusion response framework that utilizes PPO for mitigation response where the PPO framework established a strong rate of 91.3% compared to rule-based response methods. The model operates with dynamic response capability that allows it to detect new threats without compromising its low rate of false positives. The hybrid IDS approach delivers precision enhancements and provides adaptive configuration and clearer insights than standard IDS systems do. The design framework allows deployment of the system across various federated and edge environments. This study promotes the progress of next-generation intrusion detection systems which handle the growing complexity along with scale of present-day cyber dangers.

## ACKNOWLEDGMENT

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# Smoke Detection Model with Adaptive Feature Alignment and Two-Channel Feature Refinement

Yuanpan Zheng*, Binbin Chen, Zeyuan Huang, Yu Zhang, Chao Wang, Xuhang Liu
School of Computer Science and Technology, Zhengzhou University of Light Industry, Zhengzhou, China

***Abstract*—To address issues of missed detections and low accuracy in existing smoke detection algorithms when dealing with variable smoke patterns in small-scale objects and complex environments, FAR-YOLO was proposed as an enhanced smoke detection model based on YOLOv8. The model adopted Fast-C2f structure to optimize and reduce the amount of parameters. Adaptive Feature Alignment Module (AFAM) was introduced to enhance semantic information retrieval for small targets by merging and aligning features across different layers during point sampling. Besides, FAR-YOLO designed an Attention Guided Head (AG-Head) in which feature guiding branch was built to integrate critical information of both localization and classification tasks. FAR-YOLO refines key features using Dual-Feature Refinement Attention module (DFRAM) to provide complementary guidance for the both two tasks mentioned above. Experimental results demonstrate that FAR-YOLO improves detection accuracy compared to existing. There's a 3.5% Precision increase and a 4.0% $AP_{50}$ increase respectively in YOLOv8. Meanwhile, the model reduces number of parameters by 0.46M, achieving an FPS of 135, making it proper for real-time smoke detection in challenging conditions and ensuring reliable performance in various scenarios.**

***Keywords*—Smoke detection model; adaptive feature alignment; two-channel feature refinement; attention mechanism**

## I. Introduction

Fires pose a major danger to human safety, economies and ecosystems. In 2023, there were 550,000 fire incidents reported in China within just six months, resulting in 959 deaths, 1,311 injuries, and property damage amounting to 3.94 billion yuan [1]. Between 2019 and 2020, Australia endured a forest fire that lasted more than seven months, killing billions of animals and destroying over 10 million hectares of land [2]. The best way to prevent the spread of fires is to suppress the spread of fires quickly and to disperse fire sources in a timely manner. However, early flames are small and can easily be obscured, so detecting the smoke generated by fires is the optimal approach for controlling the occurrence of fire.

Early smoke detection methods [3] relied on smoke, temperature, and light sensors to detect fire particles at close range, but had limited range and were prone to environmental interference. Traditional fire smoke detection algorithms relied on manual feature extraction and machine learning classification [4], but depended on domain expertise and couldn't effectively capture image features, resulting in poor generalization and applicability.

Object detection approaches based on deep learning can automatically learn main features and details in data, offering advantages such as high accuracy and strong robustness. Convolutional Neural Networks (CNNs) extract hierarchical features layer by layer through local connections and parameter sharing mechanisms, making them highly effective for image recognition. Recently, Transformer-based architectures have achieved remarkable advances in the field of image detection. Compared to CNNs, Transformers perform well in identifying distant relationships and perceiving global information within images. However, their computational complexity is higher, and they generally require more computing resources.

Xie et al [5], introduced a forest fire smoke identification method developed with the Faster-RCNN model, which enhances the receptive field by adding a feature fusion module after each level of the feature pyramid structure. However, this region extraction-based detection method consists of two stages, leading to higher algorithm complexity and slower detection speeds. YOLO series algorithms, on the other hand, are widely used for their capability to provide precise and timely detection. Casas et al [6], has shown that the excellent applicability of YOLO algorithms in smoke detection. Zhang et al [7] introduced an enhanced YOLOv4 model that combines an attention mechanism to boost the capture of smoke feature and utilizes the K-means++ algorithm to determine the most suitable predicted bounding box scale. Despite these improvements, the model suffers from slow detection speeds, which are inadequate for the real-time requirements for smoke detection. Li et al [8], added the YOLOv5 model with a coordinate attention mechanism to strengthen the model's concentration on key smoke regions and proposed an RFB module to capture global information. However, this model still struggles with detecting small smoke targets and exhibits a low smoke recognition rate. Ouyang et al [9], introduced a new object detection model named fuse-transformer, which combines Transformer and YOLOX to use transformer to handle global context and boost the model's potential to extract feature. However, the model has issues such as excessive size, high complexity, and demanding hardware requirements.

In the past decade, numerous algorithms have been developed for fire smoke detection, yielding promising results. However, challenges persist. First, the rapid spread of fires demands prompt smoke detection. Moreover, complex environmental conditions can alter the concentration and shape of smoke, making it harder for models to accurately identify it. Objects with colors and shapes similar to smoke may also lead to false detections. Additionally, the small size of early-stage smoke features poses another significant challenge. Prior studies used complex models to improve smoke detection accuracy. But large-parameter models are complex and slow.

To meet real-time demands, some applied one stage detection models with specific feature modules. However, single stage models struggle with small targets and complex environments. We aims to attain a desirable trade-off between speed and accuracy.

This paper presents an enhanced fire smoke detection model, which is built upon YOLOv8 [10], named FAR-YOLO (Feature Alignment and Refinement-YOLO). This model attains a balance between precision and speed by incorporating innovative lightweight modules and an attention mechanism-enhanced head structure. It utilizes an adaptive upsampling module to enhance capability of capturing small smoke targets. Additionally, we have constructed an outdoor fire smoke detection dataset consisting of 3,705 real smoke images. The dataset includes images of fire smoke captured at both close and distant ranges, as well as samples from complex environments with potential interference.

In this paper, we proceed as follows: Section II presents the relevant key technologies. Section III details the innovative methods, including the design philosophy and approach of the smoke feature extraction enhancement module. In Section IV, the datasets, experimental environment, ablation experiments and comparative experiments with other detection are models introduced. Section V summarizes the work content and contributions of this paper.

## II. Related Work

### A. YOLOv8

The network design of YOLOv8 is depicted in Fig. 1. The C2F module has cross connections between its layers and splitting operations, a design that enhances gradient fluidity and boosts the model backbone's efficiency in feature extraction. By introducing PANet [11] into the neck structure, the network can transfer features from bottom to top and from top to bottom, thereby effectively fusing multi-level semantic information and geometric information. YOLOv8 includes a decoupled head structure and incorporates Distribution Focal Loss [12] and IOU Loss in the localization branch, improving its ability to detect partially occluded objects. Additionally, a Task-Aligned Assigner [13] is used for sample matching, which evaluates both object localization and classification tasks, and then determines whether an instance is a target or irrelevant sample based on weighted scores, enhancing the model's performance across multiple tasks.

### B. Attention Mechanism

The attention mechanism dynamically identifies key image regions and assigns positional weights. CBAM [14] enhances the representational power of the feature map by applying weighting to features across channel and spatial dimensions. Coordinate Attention (CA) [15] encodes the spatial coordinates to generate a coordinate weight map, which is then used to adjust the original feature map. Efficient Multi-Scale Attention (EMA) [16] addresses the accuracy loss that occur during dimensionality reduction in coordinate weight calculation by transmitting additional feature information across different regions.

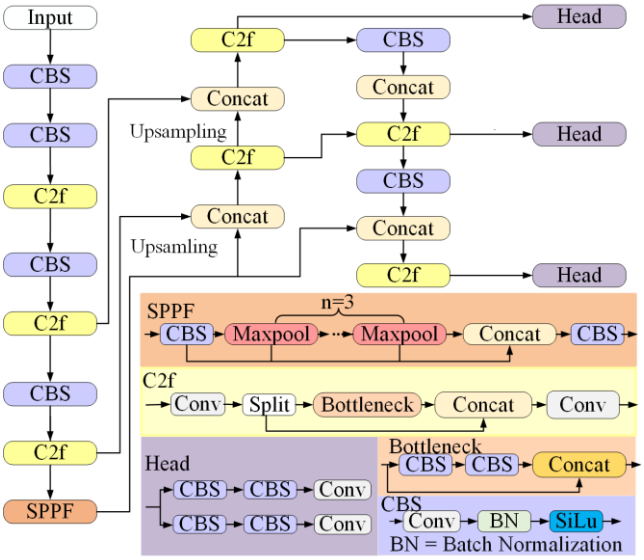



Fig. 1. Network architecture of YOLOv8.

### C. Upsampling Methods

Upsampling methods boost image resolution and restore details. Bilinear interpolation is a widely used upsampling method that estimates the value of a target point using the positional information of neighboring points. CARAFE [17] dynamically generates adaptive kernels by perceiving the content of the features to reorganize input features. Dysample [18] uses a point sampling mechanism, dynamically calculating sampling point offsets to adapt to input feature maps. Compared to kernel-based methods, Dysample achieves better results and higher computational efficiency.

## III. Improvement Scheme

The architecture of FAR-YOLO is depicted in Fig. 2. Fast-C2f is adopted instead of the original C2f structure, so that model complexity is reduced and detection speed is increased without losing accuracy. The lightweight AFAM module performs adaptive sampling during feature map reconstruction and is integrated into the upsampling process of the feature pyramid to enhance semantic information transfer across layers. In the head region, the proposed AG-Head detection head includes a feature guidance branch that consolidates key features from the two task branches. The DFRAM refines feature representations, guiding both classification and localization tasks.

### A. Fast-C2f Module

In smoke detection, the model's inference speed is crucial. The calculation formula for *Latency* is as follows:

$$Latency = \frac{FLOPs}{FLOPS} \tag{1}$$

where, *FLOPs* is a measure of the total number of float computations, and *FLOPS* signifies the amount of these operations executed each second. Considering the high similarity between channels in the feature map, Chen et al [19], proposed Partial Convolution (PConv). As shown in Fig. 3(a),

PConv convolves only a segment of continuous channel images while keeping the other channels unchanged. Compared to regular convolution, PConv decreases parameters of the model and makes detection faster.

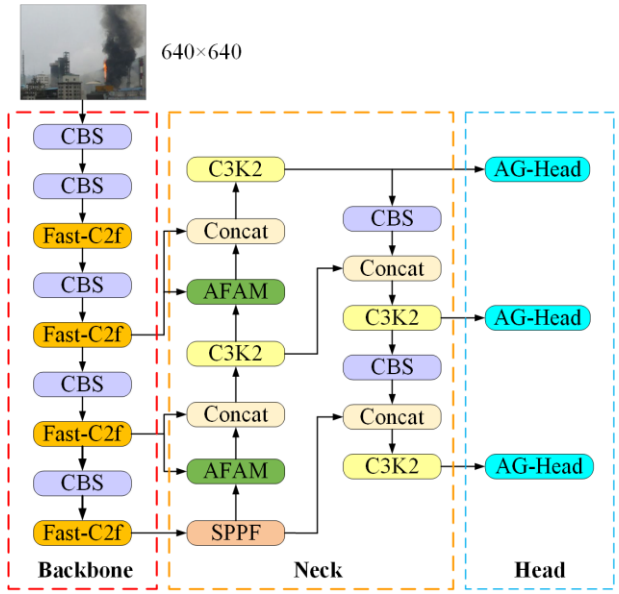



Fig. 2. Network architecture of FAR-YOLO.

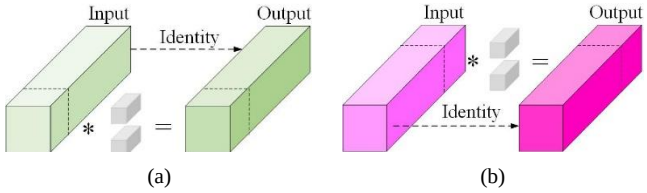



Fig. 3. Working way of Pconv: (a) Select the first quartile channel (b) Select the last quarter channel.

This paper proposes the Fast-C2f module, whose structure is presented in Fig. 4. The first partial convolution in the Fast-Bottleneck selects the first quarter of the channels for training. To avoid incomplete capture of key image information across all channels, we implemented an opposite channel selection scheme. Specifically, the second partial convolution selects the last quarter of the channels for training, as depicted in Fig. 3(b). Both of these complementary channel selection schemes enable Fast-Bottleneck to perform more comprehensive feature learning, providing the model with strong feature representation capabilities.

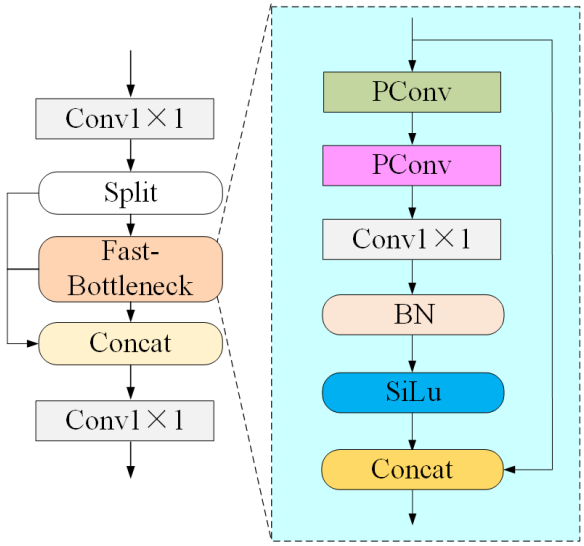



Fig. 4. Structure of Fast-C2f.

## B. Adaptive Feature Alignment Module

Early-stage smoke has a small volume and covers merely a little pixel area in the image, resulting in limited appearance information. To address this, transferring detailed semantic information from deeper layers to shallower layers can enhance feature representation for small targets. This paper adopts this approach to improve the effectiveness of feature information transfer between deep and shallow layers. To avoid interference caused by feature mismatches during the upsampling process [20], we introduce the lightweight AFAM and apply it during the upsampling stage. This module's network framework is depicted in Fig. 5.

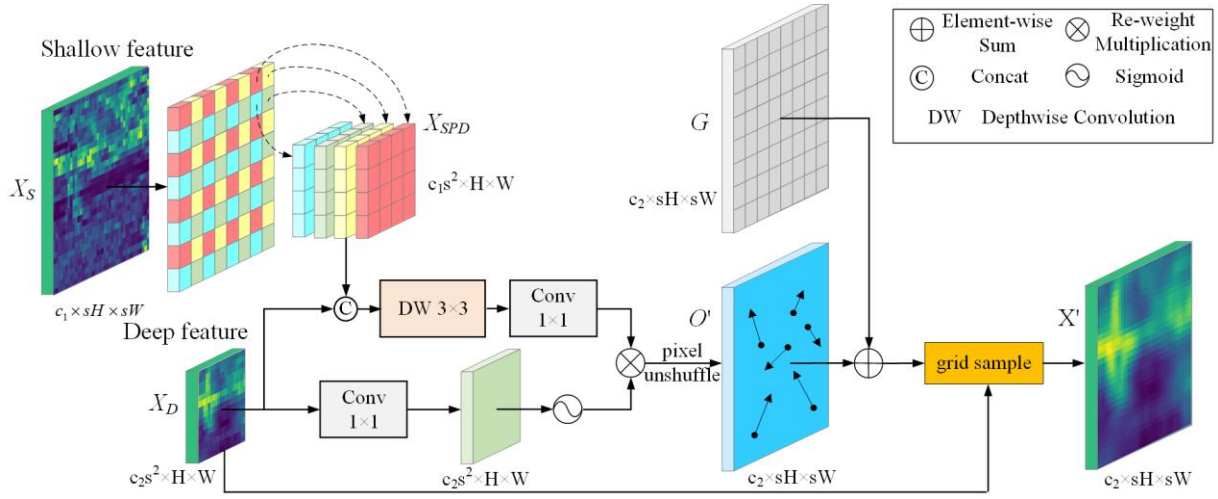



Fig. 5. Structure of AFAM.

AFAM employs point sampling for upsampling. Provided with an input feature map of size $c_2 s^2 \times H \times W$, the algorithm uses a linear layer to capture pixel neighborhood information, generating an offset flow $O$ that reflects semantic variation trends between deep and shallow features. After reshaping $O$ to $c_2 \times sH \times sW$, it combines with the sampling grid $G$ to produce the sample set $S$. The following are the formulas for the calculation of $O$ and $S$:

$$O = linear(X) \tag{2}$$

$$S = G + O \tag{3}$$

The $grid\_sample$ function is employed to resample the sample set, generating the final feature map $X'$.The formula for calculating $X'$ is shown below:

$$\boldsymbol{X}' = grid\_sample(\boldsymbol{X}, \boldsymbol{S}) \tag{4}$$

AFAM incorporates shallow image features during the generation of $O$, improving feature alignment between adjacent layers by fusing features from different levels. The geometric details from the shallow layers help guide the deeper semantic information, thereby generating a more effective offset flow. In terms of implementation, the shallow image has dimensions of $c_1 s^2 \times sH \times sW$, and we aim to adjust its dimensions to match the deep feature map. Inspired by the SPD module [21], the specific approach is as follows: AFAM divides the shallow feature map into sub-maps of size $H \times W$, then reorganizes the objects at corresponding positions in each sub-map to form a feature map with the size of $c_1 s^2 \times H \times W$. The calculation formula is as follows:

$$\boldsymbol{X}_{SPD} = \begin{cases} f(0,0) = \boldsymbol{X}_S[0:H:s, 0:W:s] \\ f(1,0) = \boldsymbol{X}_S[1:H:s, 0:W:s] \\ f(s-1,0) = \boldsymbol{X}_S[s-1:H:s, 0:W:s] \\ f(0,s-1) = \boldsymbol{X}_S[0:H:s, s-1:W:s] \\ f(s-1,s-1) = \boldsymbol{X}_S[s-1:H:s, s-1:W:s] \end{cases} \tag{5}$$

where, $X_S$ represents the shallow feature image, $s$ is the scaling factor, and $H$ and $W$ are used to signify the horizontal and vertical extent of the feature map. This method effectively preserve the detailed information in the image.

To further enhance the effectiveness of feature fusion, AFAM applies linear projection and nonlinear transformation to the deep feature map to generate a weight map. The weight map is used to adaptively balance the feature information across different layers. The calculation formula is as follows:

$$O' = Sigmoid(linear_1(X_D)) \otimes linear_2(Ct(X_D, X_{SPD})) \tag{6}$$

where, $X_D$ represents the deep feature image, $linear_1$ and $linear_2$ represent the linear projection operation on the deep feature map and the combined of Depthwise convolution (DWConv) and 1×1 convolution, respectively. $Ct$ denotes the feature concatenation operation, $\otimes$ represents matrix multiplication.

### C. Attention-Guided Head

*1) The design of AG-HEAD:* The decoupled detection head uses separate convolutional layers for localization and classification tasks. However, constrained by fixed kernel sizes, these layers only capture local features. In outdoor smoke detection scenarios, the texture features at the edges of smoke are often weak. Overemphasizing dense areas while neglecting sparse regions may misjudge the true smoke extent, reducing detection accuracy.

This paper designs AG-Head, whose network structure is shown in Fig. 6. The feature map extracts spatial feature information through DWConv, forming a feature guidance branch parallel to the other two branches. The localization and classification branches focus on learning different feature [22], while the feature-guided branch captures the features shared by both tasks during the back propagation process. The DFRAM is integrated into the feature guidance branch to fuse different types of features, providing complementary spatial information guidance for both branches. By enhancing the performance of both tasks, the model can comprehensively focus on smoke features, accurately capturing both smoke concentration and global information.

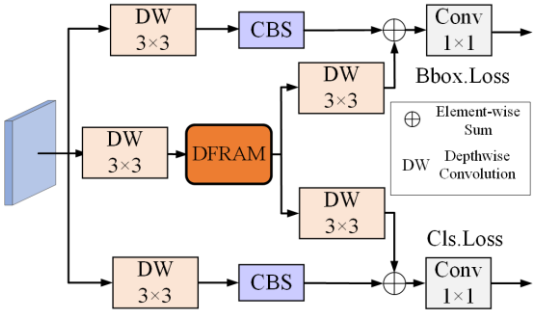



Fig. 6. Structure of AG-Head.

*2) Dual-feature refinement attention module:* To effectively fuse feature information and enhance the interaction between the two tasks, this paper proposes DFRAM, whose structure is shown in Fig. 7. This module contains two algorithms: Coordinate Feature Refinement (CFR) and Multi-Scale Feature Refinement (MSFR). CFR captures directional spatial location information, while MSFR extracts rich contextual and local features. DFRAM overlays the weight maps generated by both methods to enhance the detection head's sensitivity to smoke object concentration and spatial location.

*a) Coordinate feature refinement:* To get feature coordinate info, CFR first globally pools the input feature map vertically and horizontally. Then, CFR captures cross-channel interaction info in a special way. Since the fully connected method can't avoid the bad effects of channel dimensionality reduction and 1×1 2D convolutions aren't good enough for capturing inter-channel info, multi-kernel 1D convolutions are used to share channel info across n consecutive layers. The

calculation formulas for the global pooling operations in both directions are as follows:

$$GAP_H = \frac{1}{W} \sum_{o \le j < W} x(W, i) \tag{6}$$

$$GAP_W = \frac{1}{W} \sum_{o \le j < W} y(j, H) \tag{7}$$

The 1D convolution's kernel size is set based on the amount of channels, as the optimal kernel size is associated with the amount of channels [23]. The calculation formula is as follows:

$$n = |t|_{odd} = \left| \frac{\log_2(C)}{\gamma} + \frac{b}{\gamma} \right|_{odd} \tag{8}$$

where, $C$ indicates the count of channels, and $|t|_{odd}$ represents the odd number adjacent to $t$.

*b) Multi-scale feature refinement:* MSFR extracts image features through DWConv and Dilated convolution (DConv) with progressively increasing dilation rates [24]. The architecture processes DWConv outputs in parallel through three DConv branches with diverse receptive fields, fuses these multi-scale features with the original input, and generates spatial attention weights via 1×1 convolution and Sigmoid activation. This design captures local details and contextual patterns for enhanced feature representation. The computation process of MSFR can be described as:

$$\boldsymbol{F} = DWConv(\boldsymbol{x_{input}}) \tag{9}$$

$$MSFR_{output} = Sigmoid(Conv_{1\times1}((\sum_{i=0}^{2} DConv_r(F)) + F)) \tag{10}$$

where, $x_{input}$ is the original feature map and $F$ denotes the intermediate layer's output, $MSFR_{output}$ refers to the output feature map of MSFR. $DConv_r$ represents dilated convolutions with varying rates in the three parallel branches, where subscript $r$ indicates the dilation rate and $i$ indicates the $i$ branch in the multi-scale structure.

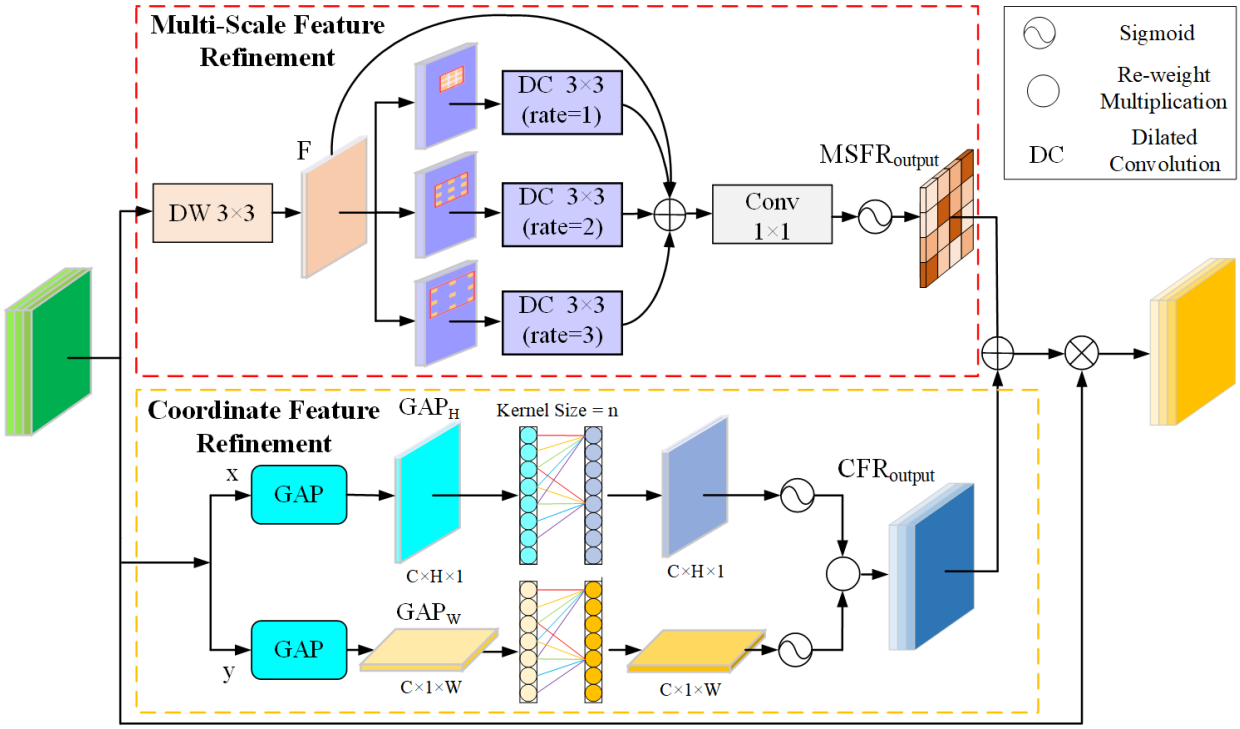



Fig. 7. Structure of DFRAM.

## IV. Experiments and Result Analysis

### A. Datasets and Annotations

Since there's a shortage of public fire smoke datasets and the lack of calibration, this paper collects smoke images and manually annotates the smoke regions to create a self-made fire smoke dataset. The smoke images are sourced from the public datasets HPWREN [25] and the Fire Detection Research Group [26], which contain real smoke objects of various sizes and in different scenes. This diverse dataset enables the model to develop strong recognition capabilities for various types of smoke. Images with low resolution or those not meeting the training requirements are excluded. The dataset is made up of 3,705 smoke images, which are randomly split into training, validation and testing sets in a 7:2:1 ratio. The dataset is formatted according to the YOLO dataset standard, and the LabelImg tool is used to annotate and create a plain text label file containing the positions and sizes of smoke targets. Some annotated image samples from the self-made dataset are shown in Fig. 8.

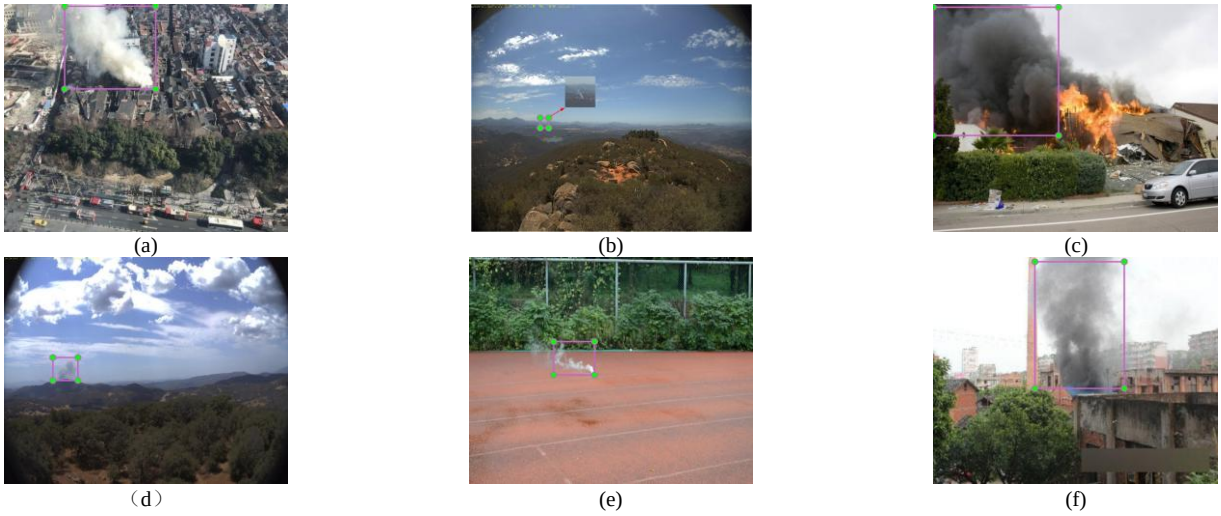



Fig. 8. Different types of labeled image samples from the self-made smoke detection dataset: (a) Large smoke; (b) and (f) show small smoke at different distances; (c) and (d) are black smoke; (e) is the smoke object in the environment of interference factors.

### B. Evaluation Metrics

This paper uses COCO metrics to evaluate the smoke detection model. Precision reflects ratio of smoke samples that are correctly recognized, while recall is the proportion of actual smoke samples detected. Another important metric is Average Precision (AP), reflecting the model's overall accuracy in smoke identification. $AP_{50}$ denotes the average precision at a threshold of 50. Additionally, Frames Per Second (FPS) measures indicates the rate at which a model can process consecutive images, and the number of parameters (Params) serves as a metric for assessing its complexity. The formulas for calculating these four metrics are presented below:

$$\mathrm{Pr}ecision = \frac{TP}{TP + FP} \tag{11}$$

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{12}$$

$$AP = \frac{1}{r}\sum_{i=1}^{r} P_i \tag{13}$$

$$FPS = \frac{1}{Time} \tag{14}$$

where, $TP$ indicates the count of smoke samples accurately detected, while $FP$ signifies the amount of irrelevant samples mistakenly labeled as smoke objects, $FN$ represents the amount of smoke samples that were missed, and $Time$ represents the time needed to process one image, which is measured in milliseconds.

### C. Experimental Environment and Hyperparameter Configuration

Experiments use Python 3.8 and PyTorch 2.0, accelerated by CUDA 11.8. Hardware includes an AMD EPYC-7663X CPU and an NVIDIA GeForce RTX 3090 GPU. The optimizer is SGD. Input images are 640×640. The model is trained for 300 iterations, using batches of 16 and with a learning rate initially set to 0.001.

### D. Comparative Experiment of Adaptive Feature Alignment Module

The upsampling operator can augment the model's proficiency in capturing essential information, but it also introduces complexity. Therefore, this section compares the AFAM module with the advanced lightweight CARAFE module and Nearest Neighbor Interpolation (NNI). The comparison results, presented in Fig. 9, demonstrates that the AFAM module achieves a Precision of 88.7% and an $AP_{50}$ of 89.3% with fewer Params and FPS. Although CARAFE can achieve similar accuracy, it costs nearly twice as much in terms of Params and FPS compared to AFAM.

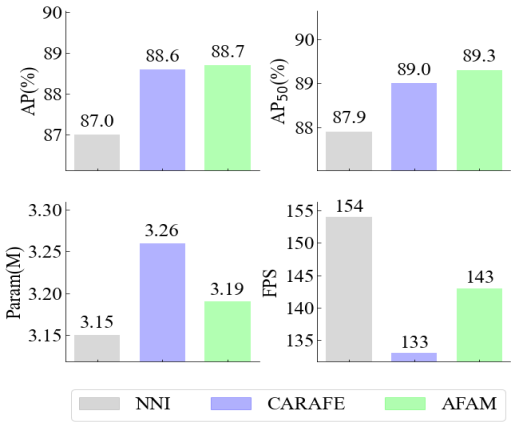



Fig. 9. Experimental comparison results of three upsampling methods under four different evaluation metrics: AP, $AP_{50}$, Params, and FPS.

### E. Experimental Analysis of Dual-channel Feature Refinement Attention Module

This section investigates the influence of diverse dilation rate combinations of DConv in MSFR on the final results. Additionally, to evaluate the impact of the DFRAM, Several mainstream attention mechanisms are used for comparison with it.

*1) Comparison experiments of different expansion rates:* To study the impact of dilation rates on accuracy in MSFR, three combinations of dilation rates were tested: [1, 2, 3], [2, 4, 6], and [4, 8, 12]. These combinations were applied to MSFR, and experiments were conducted using the YOLOv8 network integrated with AG-Head on the self-made dataset. The comparison results are presented in Table I, illustrating that the [1, 2, 3] combination reaches the superior detection performance. While larger dilation rates capture a larger receptive field, they also result in losing local details, which reduces the model's capacity for recognizing small objects.

TABLE I. DETECTION RESULTS BASED ON DIFFERENT DILATION RATE COMBINATIONS' CONFIGURATIONS

| *Rates* | *Precision (%)* | *$AP_{50}$ (%)* |
|---|---|---|
| [1,2,3] | 89.3 | 90.5 |
| [2,4,5] | 88.8 | 90.3 |
| [4,8,12] | 88.6 | 90.0 |

*2) Comparative experiments with different attention modules:* This section compares the performance of DFRAM with the CA, CBAM, and EMA. These attention modules are separately introduced into the YOLOv8 network integrated with AG-Head, and the attention maps generated by them are used to assist in task judgment. As shown in Table II, DFRAM shows the best performance.

TABLE II. DETECTION RESULTS BASED ON DIFFERENT ATTENTION MODULES' CONFIGURATIONS

| *Attention module* | *Precision (%)* | *$AP_{50}$ (%)* |
|---|---|---|
| CA | 88.1 | 89.7 |
| CBAM | 88.9 | 90.1 |
| EMA | 89.2 | 90.3 |
| DFRAM | 89.3 | 90.5 |

## F. Comparative Experiments

To assess the proposed improvements' effectiveness, this section conducts comparative experiments using the self-made smoke dataset, along with mainstream object detection methods from recent years. These methods include YOLO series detection algorithms such as YOLOv3 [27], YOLOv5 [28], and YOLOv7-tiny [29]. Additionally, the comparison includes the two-stage detection method Faster-RCNN [30] and cutting-edge algorithms based on the Transformer framework, such as Dino [31] and Dab-detr [32].

The experimental information is detailed in Table III. The YOLO series detection algorithms achieve higher accuracy than Faster-RCNN while requiring fewer parameters. Although the YOLO algorithms fall short of Transformer-based models in performance, their superior detection speed makes them more fitting for real-time smoke detection scenarios. Both YOLOv7-tiny and YOLOv8 achieved Precision exceeding 86.0%, with $AP_{50}$ surpassing 87.6%. However, YOLOv7-tiny has parameters in an amount close to twice that of YOLOv8. The FAR-YOLO model not only achieves the best accuracy among the models tested but also requires fewer parameters than YOLOv8, demonstrating that FAR-YOLO offers the best overall performance.

TABLE III. COMPARATIVE EXPERIMENTS OF DIFFERENT ADVANCED MODELS

| **Compare Models** | ***Precision (%)*** | ***Recall (%)*** | ***$AP_{50}$ (%)*** | ***Params (M)*** | ***FPS*** |
|---|---|---|---|---|---|
| Faster-RCNN (ResNet50) | 80.2 | 76.1 | 81.4 | 28.55 | 18 |
| YOLOv3n | 83.0 | 82.3 | 84.4 | 8.67 | 120 |
| YOLOv5n | 85.8 | 83.6 | 87.0 | **1.89** | 135 |
| YOLOv7-tiny | 86.1 | 84.0 | 87.6 | 6.20 | 123 |
| YOLOv8n | 87.0 | 84.3 | 87.9 | 3.15 | **156** |
| Dino | 89.7 | 87.3 | 91.2 | 47.00 | 17 |
| Dab-detr | 88.8 | 87.6 | 90.0 | 44.00 | 27 |
| FAR-YOLO | **90.5** | **87.9** | **91.9** | 2.69 | 135 |

A scatter plot intuitively compares model performance, with $AP_{50}$ on the vertical axis and the number of Params on the horizontal axis. In the scatter plot, a model positioned further to the left indicates fewer parameters and lower computational complexity, while a position further up suggests higher precision. As illustrated in Fig. 10, Transformer-based models, despite their high precision, are located in the top right position due to their large number of parameters. This implies high computational resource demands, making them prone to deployment difficulties and slow operation on edge devices. In contrast, FAR-YOLO achieves a higher $AP_{50}$ with fewer parameters, placing it in the top left region. Among models with similar parameter counts, FAR-YOLO is positioned higher, indicating superior performance at the same parameter level. Thus, FAR-YOLO strikes a good balance between precision and computational complexity, suits edge deployment, and can deliver ideal detection accuracy on resource-constrained edge devices with lower computational and storage costs.

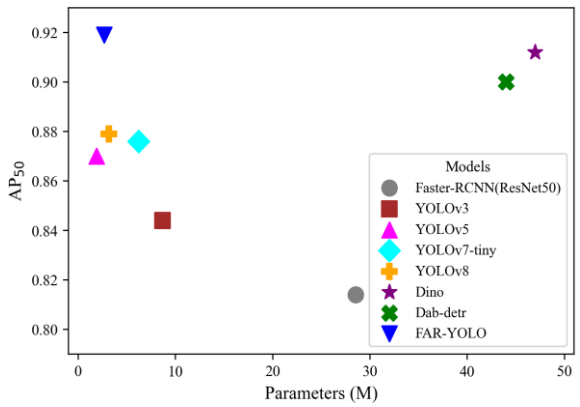



Fig. 10. Scatter plot of different models.

## G. Ablation Experiments

This section presents ablation experiments on the self-made fire smoke dataset to assess the effect of the proposed improvements on model performance. The ablation experiment results are depicted in Table IV.

TABLE IV. ABLATION EXPERIMENTS FOR DIFFERENT MODULES

| Experiment Group | Improvement Scenarios | | | Evaluation Metric | | | |
|---|---|---|---|---|---|---|---|
| | Fast−C2f | AFAM | AG−Head | *Precision (%)* | *Recall (%)* | *$AP_{50}$ (%)* | *FPS* |
| 1 | | | | 87.0 | 84.3 | 87.9 | 156 |
| 2 | ✓ | | | 87.1 | 84.9 | 88.4 | **161** |
| 3 | | ✓ | | 88.7 | 86.1 | 89.3 | 143 |
| 4 | | | ✓ | 89.3 | 86.2 | 90.5 | 137 |
| 5 | | ✓ | ✓ | 89.7 | 87.6 | 91.3 | 128 |
| 6 | ✓ | ✓ | ✓ | **90.5** | **87.9** | **91.9** | 135 |

In Group 2, the opposing channel allocation scheme of Fast-C2f increased the detection speed while maintaining the model's precision. The AFAM module enhanced the effectiveness of feature information transfer between different layers, resulting in a 1.4% increase in $AP_{50}$ for Group 3. The introduction of the AG-Head, which includes the feature guidance branch and the DFRAM, resulted in Precision increasing by 2.3% and $AP_{50}$ by 2.6% in Group 4. Group 5 combined AFAM and AG-Head, achieving a greater performance improvement compared to individual modules, with an $AP_{50}$ of 91.3% and Recall of 87.6%, demonstrating that combining multiple modules yields better results. Finally, Group 6, which combined all three modules, showed a 4.0% increase in $AP_{50}$ compared to Group 1, achieving a Recall of 87.9% and achieving a Precision of 90.5%. Although the FPS slightly decreased, it still reached 135 frames per second, reaching real-time detection requirements. Overall, the performance of the improved model demonstrated significant improvements.

The precision and recall curve evaluates precision and also takes recall into account across different thresholds, offering a comprehensive measure of model performance. Fig. 11 displays the precision and recall (pr) curves for the baseline model and various improvements. It is clear that the PR curve of the enhanced model largely overlaps with that of the baseline model, demonstrating that, at the same recall rate, the improved model achieves higher precision.

### *H. Detection Performance and Analysis*

*1) Visualization of improvement effects:* To more effectively prove the validity of the proposed improvements, we use the YOLOv7tiny, YOLOv8 and FAR-YOLO models to detect smoke in fire scenes. As shown in Fig. 12, the improved model performs well in detecting large smoke plumes. The baseline model struggles to effectively recognize the entire smoke in scenarios involving large smoke with uneven concentration, often mistakenly dividing it into two parts. In contrast, the improved model captures richer contextual information, allowing it to accurately enclose the entire smoke plume with the detection box. Fig. 13 further demonstrates that the enhanced model surpasses the baseline in detecting small smoke targets. Additionally, under strong external light interference, the improved model can still accurately locate the smoke, while the baseline model fails to detect it, particularly in conditions of strong lighting and small smoke.

*2) Visualization of smoke feature extraction capabilities:* To better analyze the model's proficiency in smoke feature extraction, This paper adopts heatmaps to display the model's focus to different regions of the image during detection. The attention of a region is related to its color; the warmer the color, the higher the attention, indicating that the higher the attention, the greater the contribution of the region's features to the prediction result. As shown in Fig. 14, group (c) is the baseline model YOLOv8, and group (d) is the improved model FAR-YOLO. The improved model allocates more attention to the smoke region than the baseline model and the high-attention areas align with the contours of the complex-shaped smoke. This indicates that the improved model can accurately locate the region of interest, demonstrating superior performance.

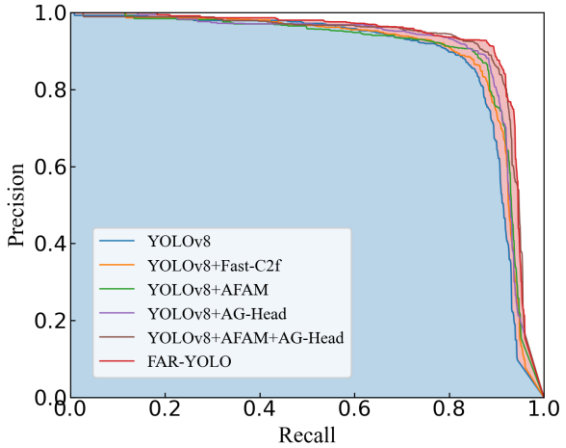
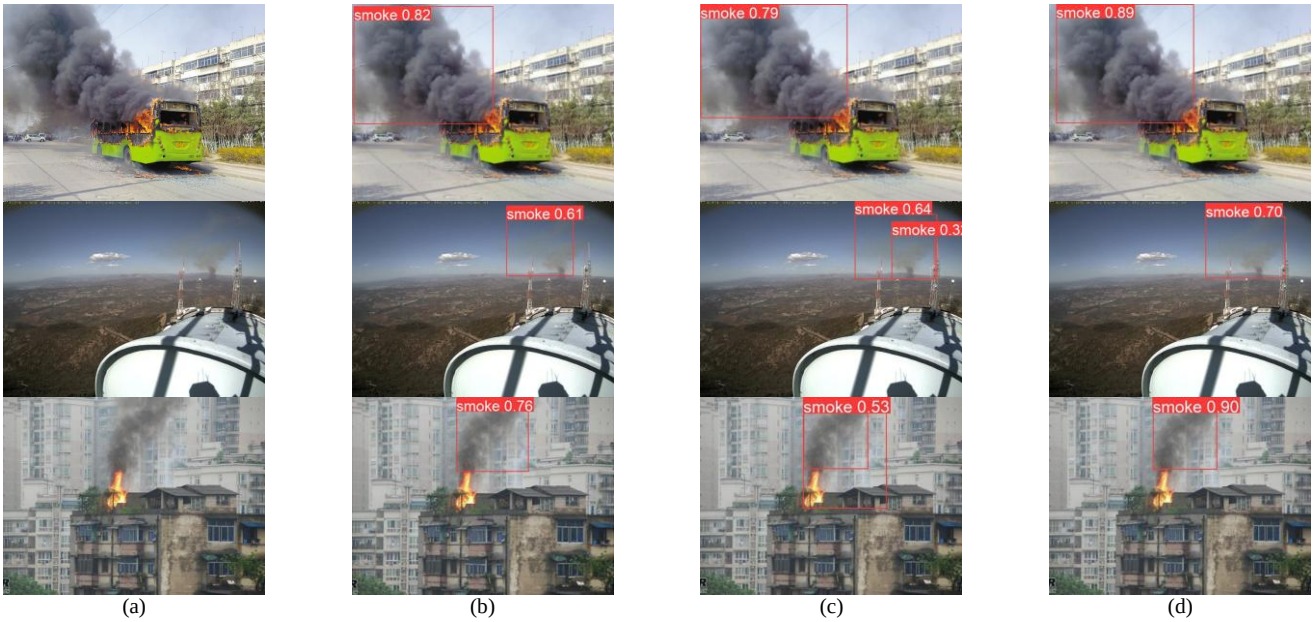
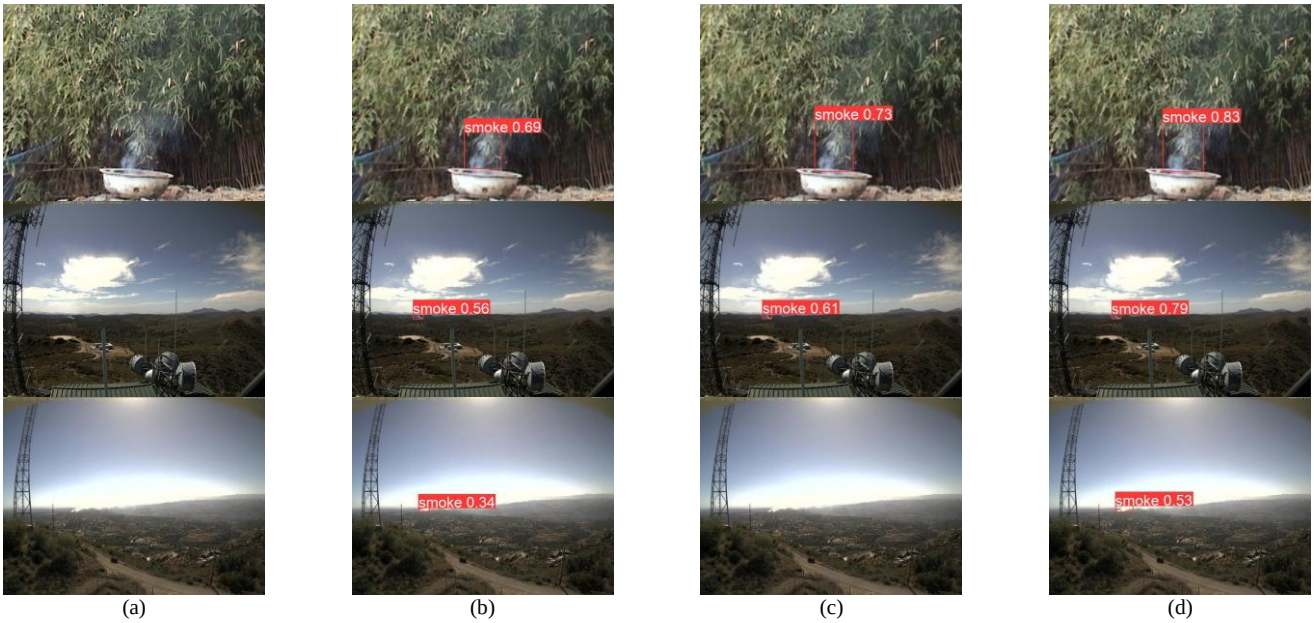



Fig. 11. Comparison of precision and recall (PR) curves with Different modules.



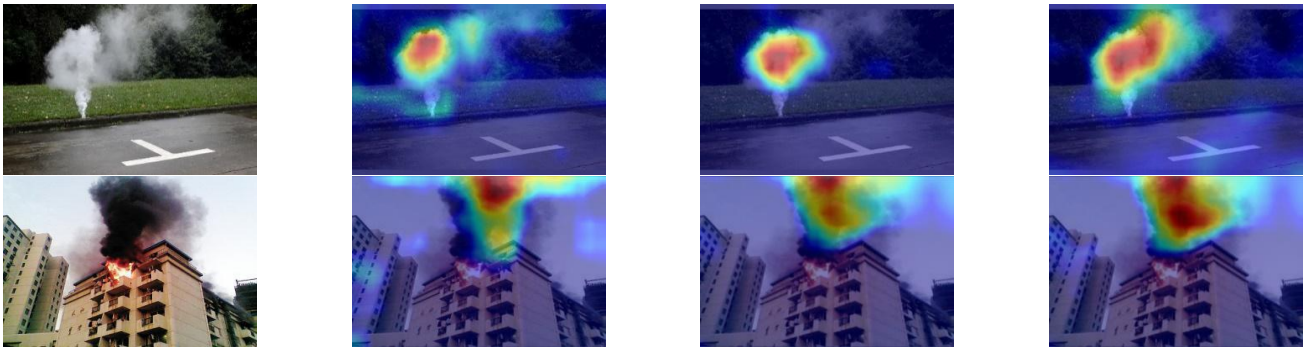

(a) (b) (c) (d)

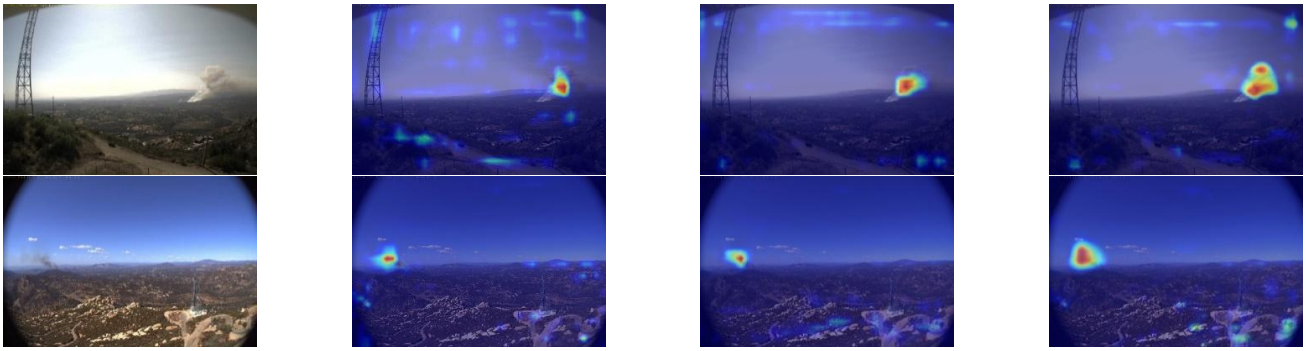
Fig. 12. Medium and large-scale smoke detection performance:(a) Original images;(b) YOLOv7tiny;(c) YOLOv8;(d) FAR-YOLO.




(a) (b) (c) (d)

Fig. 13. Early and small-scale smoke detection performance:(a) Original images;(b) YOLOv7tiny;(c) YOLOv8;(d) FAR-YOLO.





(a) (b) (c) (d)

Fig. 14. Heat maps showing the prediction of different models for smoke objects at near and far distances:(a) Original images; (b) YOLOv8; (c) FAR-YOLO.

## V. CONCLUSION

This paper creates a multi-scene smoke dataset from public sources and introduces FAR-YOLO, an enhanced YOLOv8-based model. The model employs partial convolutions with two channel allocation strategies to build the Fast-C2f module, reducing complexity and boosting speed. The AFAM module is integrated into the upsampling process, uses adaptive alignment and resampling to strengthen the correlation between deep semantic and shallow positional features, improving small object detection. The AG-Head is introduced, featuring a feature-guided branch that extracts critical feature information from different task branches. The embedded DFRAM in this branch captures richer context and localization info, enhancing smoke concentration and scale judgment. Experiments show the model effectively detects multi-scale smoke in various scenes, with Precision and $AP_{50}$ reaching 90.5% and 91.9%, respectively, and Recall achieving 87.9%. Additionally, the model reduces the parameter count by 0.46M and achieves a FPS rate of 135. The model effectively balances detection accuracy and speed, excelling in real-time smoke detection.

## DATA AVAILABILITY

Data used for this article were collected by the research team and will be given to other researchers upon request.

## CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

## ACKNOWLEDGMENT

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# Design and Modeling of a Dynamic Adaptive Hypermedia System Based on Learners' Needs and Profile

Mohamed Benfarha[1]*, Mohammed Sefian Lamarti[2], Mohamed Khaldi[3]
A Research Team in Computer Science and University Pedagogical Engineering-Applied Mathematics and Computer Science (AMCS) / Higher Normal School of Tétouan, Abdelmalek Essaadi University, Morocco[1, 2]
A Research Team in prt, Abdel Malek Essaadi University, Morocco[3]

***Abstract*—This study presents the design and modeling of an adaptive hypermedia system, capable of dynamically adjusting to the needs and characteristics of each learner according to their profile. In the digital age, where digital content must respond to varied profiles and adapt to learners' preferences and skills, this system offers a personalized approach that improves the learning and interaction experience. This personalized approach aims to enrich the learning and interaction experience with learning environments. This work consists of analyzing the different types of learner profiles, in order to identify the key criteria for effective personalization. Based on this, the authors developed a model of an adaptive and dynamic hypermedia system, capable of adapting in real time. To ensure a clear and coherent structure, the use of UML (Unified Modeling Language) modeling is increased. Preliminary results show that this system offers a relevant and targeted experience thanks to learner engagement and satisfaction, making learning both more relevant and more enjoyable. This work paves the way for future research on the optimization of hypermedia systems by further integrating the individual behaviors of learners, in a truly adaptive learning environment, which values the potential of each learner.**

***Keywords*—Design; adaptive hypermedia; learning styles; user modeling; UML models**

## I. INTRODUCTION

Currently, hypermedia learning systems, whether online educational platforms, interactive digital courses or distance learning tools, interactive digital environments occupy a central place in modern education [1], [2]. By combining texts, images, videos, sounds and hypertext links to enrich the user experience [3]. These systems offer a richer learning experience than traditional media. However, despite their advantages, the majority of these systems lack sufficient adaptability to personalize the experience according to users, their context and their learning styles [4]. Most of them have a major limitation: their rigidity. Few are able to truly adapt to the particularities of each learner, their learning style, their skill level or their context of use. Faced with this observation, dynamic adaptive learning systems are emerging as a promising solution and represent a significant evolution in online learning and knowledge management [5]. The integration of artificial intelligence techniques, recommendation technologies in platforms and recommendation algorithms, allows to meet the growing need for individualization in education and takes into account the individual differences of users, their learning preferences, their skill levels and their context of use, while offering personalized, effective and optimized learning experiences and adjusting the content and interface in real time to improve the learning experience and effectiveness. Personalize the educational experience in real time, adjusting the content, the difficulty of the exercises, and even the user interface to optimize engagement and learning effectiveness [6], [7]. This individualized approach meets a growing need in the educational field, where learners have different rhythms, preferences and objectives [8], [9]. However, designing such a system requires a flexible architecture and complex decision logic, capable of processing heterogeneous data (such as user performance, interactions or history) to generate relevant learning paths [10], [11]. This is where Unified Modeling Language (UML) plays a key role. By providing a visual and structured representation of system components, interactions between actors, and adaptation mechanisms, UML allows these technical requirements to be formalized while ensuring a robust and scalable design [12], [13]. Using UML for the design of personalized and flexible educational systems is crucial. Thanks to a clear representation of the dynamic structure, complex interactions, and adaptation mechanisms, UML allows the specification of both functional requirements such as content customization and non-functional requirements such as performance and security [14], [15], [16], [11], [17], [18], [19], [20], [21] and [22].

This research aims to design an innovative model of a dynamic adaptive hypermedia system capable of adjusting in real time to the specific needs of users. To achieve this, the working approach in this study is based on a UML modeling defining the components, interactions and adaptation mechanisms necessary for the personalization of the user experience in real time and complete that integrates three essential dimensions: the management of learner profiles (skills, preferences and learning history), the adaptation mechanisms (personalization rules and content recommendation algorithms), and the underlying software architecture (functional modules, data flows and user interfaces). The study is structured in four main parts: we will start by drawing up an in-depth state of the art of existing adaptive hypermedia systems and their current limitations; we will then present our design methodology with the different UML diagrams (use cases, classes and sequences); then we will analyze the preliminary results demonstrating the impact of adaptivity on learner engagement; Finally, we will

explore future perspectives, particularly the advanced integration of artificial intelligence to refine personalization. Through this study, we aspire to contribute significantly to the development of intelligent learning environments where technology serves the development of each learner's individual potential.

This research adds to recent studies on adaptive hypermedia systems [4], [6], [8], while presenting notable methodological advances. Unlike current methods that rely mainly on adjustment based on fixed profiles [9], [12] or established guidelines [15], our model proposes a more advanced dynamic approach, drawn from recent advances in the field of educational AI [17], [20]. In contrast to traditional approaches that modify content linearly [5], [7], our device incorporates a double adaptation: both of learning trajectories and user interfaces, thus filling two gaps identified in the publications [10], [13]. Furthermore, the proposed UML model provides a more exhaustive formalization than the architectures detailed in [11], [14]. Explicitly incorporating instantaneous feedback and contextual adjustment processes, often neglected in previous research. This approach offers us the opportunity to address still unresolved issues in the field, such as the administration of changes between various levels of complexity and the harmony between system direction and student independence.

## II. Theoretical Framework

The theoretical framework of our work on the design and modeling of a dynamic adaptive hypermedia system is based on several key areas that include learning theories, system adaptability, hypermedia technologies, and static and dynamic interactive system modeling approaches. This framework is based on theories and concepts from artificial intelligence, software engineering, interface customization, and pedagogy.

### A. Learning Theories and Adaptive Systems

Learning theories are at the heart of adaptive systems, as they influence how content should be structured and presented. They play a central role in the design of adaptive learning systems, especially in hypermedia environments. They provide the conceptual foundations that guide the adaptation of learning paths according to learners' profiles and needs. These theories explain how individuals acquire, process, and retain information, which helps to structure and personalize learning experiences. Learning theories include cognitive, constructivist, and behaviorist approaches, each with a specific impact on the design of adaptive learning environments [11], [23], [24]. Some of the most influential theories include:

*1) Multimodal and adaptive learning:* Multimodal learning theory proposes that learners process information more efficiently when it is presented in multiple forms, such as text, images, videos, interactive simulations, etc. This approach takes into account the fact that individuals have diverse preferences in terms of sensory modalities (visual, auditory, kinesthetic), which directly influences the design of adaptive learning systems. This theory makes it possible to design learning environments that can adapt to different learning styles [25], [26]. Adaptive hypermedia systems exploit this theory by offering a variety of teaching resources and adjusting content according to individual learners' preferences.

*2) Cognitive and constructivist theories of learning:* Cognitive and constructivist theories of learning provide fundamental foundations for the design of adaptive hypermedia systems. These theories share a common vision that learning is an active process where learners construct their own knowledge by integrating new information into their existing cognitive structures.

Indeed, cognitive theories focus on how learners perceive, process, and store information. This theory suggests that learners organize information in their long-term memory through processes such as encoding and recall [27], [28]. Adaptive hypermedia systems incorporate these principles by structuring content to avoid cognitive overload and by offering contextual help or additional explanations based on learners' answers or mistakes [11].

Constructivist theories, such as those of Piaget and Vygotsky, emphasize the active role of the learner in the construction of knowledge that allows him to build his own understanding of the world according to his experiences [23]. In an adaptive system, this implies that content must adjust according to the learner's skill level and learning style, as does modular content, which adjusts to the user's choices to meet their immediate interests or needs. By allowing the learner to actively explore resources, often in interactive environments, such as immersive environments or simulations, where the learner can manipulate variables and observe the results [11].

Cognitive and constructivist theories strongly influence the design of adaptive hypermedia systems by directing their ability to provide personalized, interactive, and contextual learning. These theories help to understand learners' needs and design tools that can dynamically adapt to their progress and preferences, enhancing the effectiveness of learning in modern digital environments.

*3) Socioconstructivist learning and adaptation:* Socioconstructivist theories emphasize the crucial role of social interactions in the learning process. These theories, inspired mainly by the works of Vygotsky and other researchers, postulate that learning is a social and contextual activity where individuals construct their knowledge through their interactions with others, cultural tools, and their environment [29], [23] . In the context of adaptive learning systems, these principles translate into the integration of interfaces, collaborative tools, and coping mechanisms that promote these interactions [11], [30].

*4) Theory of Experience-Based Learning (Learning by Doing):* The idea that individuals learn best by practicing and experiencing real-life situations is at the heart of modern approaches to learning and provides a solid basis for the design of adaptive learning systems [31], [32]. This perspective draws on several theories and pedagogical frameworks, including experiential learning, situated cognition, and constructionism. Indeed:

Kolb's theory of experiential learning proposes that learning occurs through a cycle of concrete experiences followed by reflections and applications [33]. Adaptive systems can leverage this theory to provide immersive learning experiences tailored to learners' needs. Adaptive systems use this cycle to provide interactive activities, simulations, and assessments that promote active learning.

Situated cognition suggests that learning is most effective when it takes place in contexts close to those where the knowledge will be applied [30]. Adaptive learning environments draw inspiration from this theory to create realistic scenarios, immersive tasks, or serious games where users can directly apply the skills.

According to the theory of constructionism, individuals learn by creating concrete artifacts [34]**.** Adaptive systems allow learners to build digital projects while receiving real-time feedback to adjust their actions.

The integration of real-life practices and experiences into adaptive systems is based on a sound theoretical foundation and offers an effective approach to meeting the varied needs of learners. By combining simulation, personalization and feedback, these systems promote active and relevant learning, making users better prepared to apply their knowledge in real-world contexts.

### *B. Adaptive Systems and Hypermedia*

*1) Concept and applications:* Adaptive systems in education aim to adjust learning paths according to the specific characteristics of learners, such as their level of competence, learning preferences, or learning pace. [35], [36], [37], [38]. Hypermedia systems refer to non-linear information systems where users can navigate between multimedia resources, often interactively. These systems offer great flexibility and a richer learning experience compared to traditional teaching materials (books or lectures) [39], [40], [41], [42], [43].

When the two systems are combined, they leverage digital media (text, image, video, sound, etc.) to provide user-friendly educational resources and materials. Their integration helps create powerful learning environments that provide a personalized, multi-modal experience. In these environments, the educational content is not only adapted according to the learner's profile, but is also interactive and immersive, thanks to the use of multimedia technologies. Adaptive systems seek to meet the individual needs of users by adjusting resources based on their behavior, context, and preferences. These systems are often used in e-learning, content recommendation, and knowledge management applications. Indeed, adaptive hypermedia systems are based on the idea that the user can navigate through different types of content (text, video, image, etc.), with the possibility that each resource is adjusted according to the user. Such a system must incorporate the ability to analyze user interaction and adjust content or navigation paths in real time [44], [45], [11], [46], [47].

*2) Characteristics of adaptive systems:* An adaptive system is a system that is able to modify its behavior or responses based on user interactions or characteristics. In an educational context, this includes several dimensions [48], [49], [50], [51].

Performance-based adaptation: The system adjusts content based on the learner's previous actions, such as right or wrong answers in a quiz, or how quickly they complete a task.

Preference-based adaptation: Some adaptive systems adjust the path based on a learner's learning styles (visual, auditory, kinesthetic), interests, or priorities;

Context-based adaptation: The system can adjust its behavior according to the learning context, which could include the time of day, the environment, or the device used (computer, tablet, mobile phone).

These systems use adaptation algorithms, learner profiling models, and feedback mechanisms to deliver a personalized journey.

## III. RESULTS

*1) Unified Modeling Language (UML):* Dynamic adaptive hypermedia systems (SHAD) meet the diverse needs of users by adjusting their content, navigation, and presentation based on criteria such as preferences, context, and behavior. UML modeling is a standardized and powerful approach to representing, designing, and documenting software (and sometimes non-software) systems using graphical diagrams [51]. UML makes it possible to visualize the structure, behavior and interactions of the different components of a system, thus facilitating communication between stakeholders, both technical and non-technical. UML is widely used in software engineering to analyze functional and non-functional requirements, design robust software architectures, and document existing or developing systems [52], [53], [54], [55], [56]. Through this study, we propose four diagrams, including two structural diagrams (class diagram and use case diagram) and two behavioral diagrams (sequence diagram and activity diagram).

*2) The class diagram:* The class diagram is an essential tool for modeling the static structure of software systems. By clearly defining classes, their attributes, methods, and relationships, it plays a central role in object-oriented design. This diagram is particularly useful in educational contexts, where it allows to model complex learning environments, integrating various roles (teachers, learners, courses, content, etc.). Our diagram has eleven classes.

*3) The Use case diagram:* The use case diagram is an essential tool for understanding and modeling the interactions between a system and its users. Its simplicity and expressiveness make it a powerful communication tool to identify key features of the system while ensuring that they meet the needs of the stakeholders

*4) The activity diagram:* The activity diagram is a graphical representation used in the UML language to model workflows or processes in a system. It highlights the sequence of activities, decisions, bifurcations, and synchronizations in a given process.

*5) The sequence diagram:* The sequence diagram is an essential tool for modeling dynamic scenarios in a system. By showing how actors and components interact over time, it

makes it possible to design, analyze and optimize complex processes. This methodology is particularly useful in educational contexts, where user-system interaction is crucial to provide a personalized and effective experience.

## IV. Discussion

In this section, we discuss the modeling results in the form of a description of the various proposed diagrams:

### A. The Class Diagram

The Fig. 1 presents the class diagram. It includes eleven interconnected classes, each playing a key role in meeting the educational needs of learners, teachers, and administrators, in the following format:

The LearningEnvironment class: This class is the nerve center of the learning environment system, managing the entire learning process. It has a unique identifier (id), is associated with a specific course, and stores the learner's environment preferences. The LearningEnvironment class uses these preferences to configure itself, recommend activities based on the learner's learning style (getActivityRecommendations), and evaluate the suitability of the current environment (evaluateEnvironment). For example, assessment Environment (preferences: Environment Preferences): bool: evaluates the current learning environment based on the learner's preferences and returns a Boolean value indicating whether the environment is suitable. These operations ensure that the learning experience is tailored to the needs of each learner, making LearningEnvironment the "brain" of the system that coordinates all interactions.

The LearningStyleProfile class: This class captures a learner's preferred learning style, allowing for personalized learning experience. It has a unique identifier (id) and is associated with a specific learner. The profile stores the learner's preferred learning styles (e.g., "Visual Learner", "Auditory Learner") and their preferred learning environment settings (environmentPreferences). For example, if a learner prefers a custom environment, this information will be stored in the EnvironmentPreferences attribute.

The LearningStyleProfile can be updated with new learner data (updateLearningStyles) and can determine the optimal learning environment for the learner based on their preferences (getOptimalEnvironment). This allows LearningEnvironment to tailor the learning experience to the individual needs of the learner, ensuring a more effective and engaging learning environment.

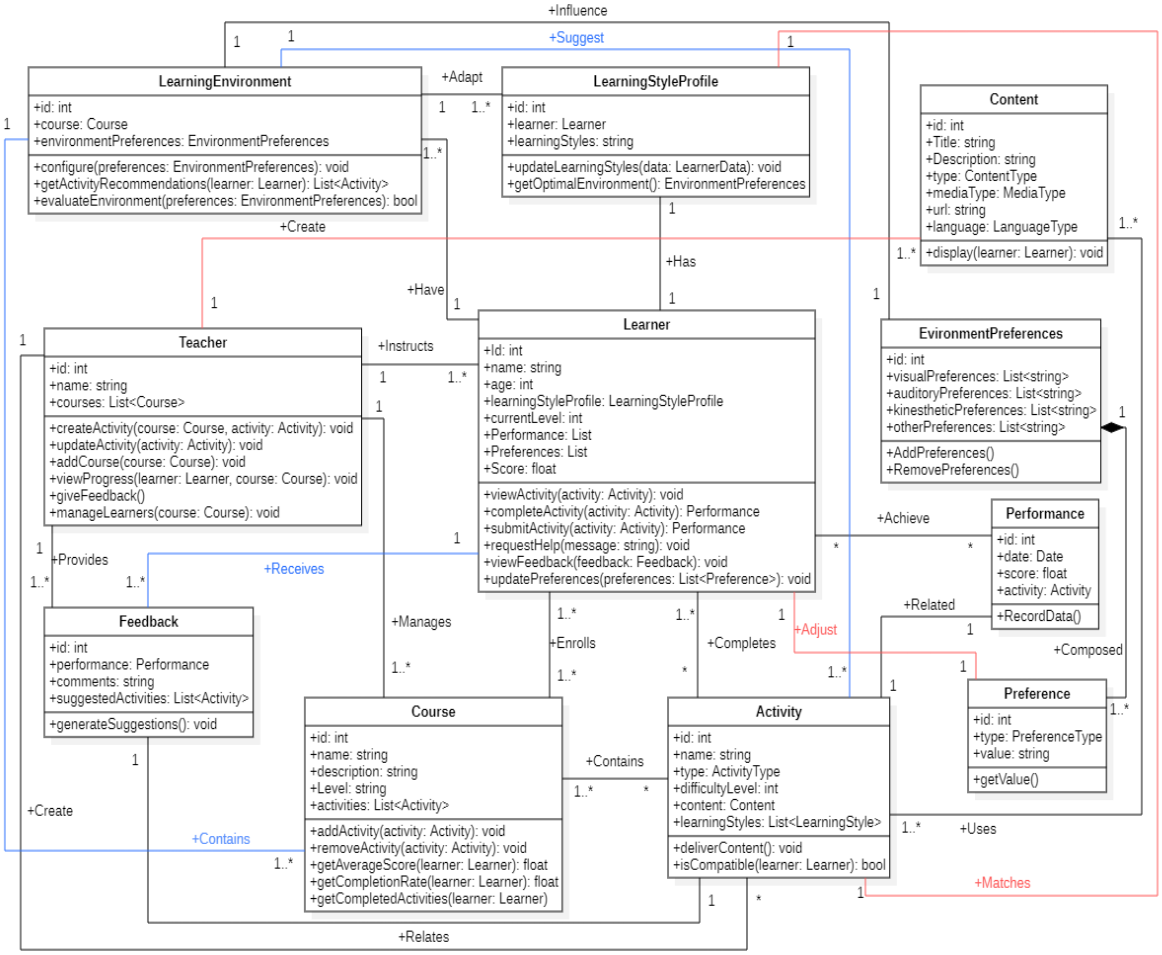


Fig. 1. Class Diagram.

Content Class: This class represents learning materials, including text, videos, images, quizzes, and other resources. The content provides the basic learning materials that learners interact with to acquire knowledge and skills. In this class, to define the different types of learning content, media formats, and languages in your system, we had to use enumerations. For example, the ContentType enumeration lists the different types of content such as "Video," "Text," and "Quiz." Similarly, the MediaType enumeration defines media formats such as "Video/mp4" and "text/html," while the LanguageType enumeration lists supported languages such as "English," "Spanish," and "French." Using enumerations for these attributes ensures that the values are consistent, readable, and easy to manage. Using enumerations makes the code more readable by providing meaningful names for the values instead of using raw strings. Enumerations also prevent invalid attributes from being accidentally assigned invalid values. Also, if we need to add new content types, media types, or languages, we only need to update the enumeration, not all the places where we use those values. Finally, you don't need to create another class with these names. For operations. Learner Void displays the content item to the learner.

The Learner class: This class represents the user of the learning environment system, the individual who learns and interacts with the system's features. The Learner can view the activities (viewActivity), complete them (completeActivity), submit them for grading (submitActivity), ask the teacher for help (requestHelp), and view the feedback provided by the teacher (viewFeedback). They can also update their preferences for the learning environment (updatePreferences). For example, a learner can complete an activity (completeActivity), receive feedback on their performance (viewFeedback), and then update their preferences (updatePreferences). The Learner is the central actor in the learning environment, engaging in activities, receiving feedback and monitoring their progress.

The EnvironmentPreferences class: This class captures a learner's preferences related to their learning styles, allowing them to customize their experience. It has a unique identifier (id) and stores a list of preferences categorized by learning style: visual (visualPreferences), auditory (auditoryPreferences), kinesthetic (kinestheticPreferences), and other (otherPreferences). For example, a learner may have visual preferences for learning via diagrams and videos, auditory preferences for listening to lectures and podcasts, and kinesthetic preferences for hands-on activities. The EnvironmentPreferences class allows you to add new preferences (addPreference) and remove existing ones (removePreference). This flexibility allows learners to adjust their preferences as needed, ensuring a personalized learning experience that aligns with their individual learning styles.

Performance class: This class records a learner's performance on a specific activity, by entering their score and the date the activity was completed. It also retains a link to the activity itself. For example, a Performance record might show that a learner scored 85% on an activity on a specific date. This class allows the system to track the learner's progress, identify areas where they may need additional support or guidance, and provide personalized feedback.

Activity class: This class represents a specific task or learning activity that learners participate in, such as taking a quiz, watching a video, or participating in a discussion. It has a unique identifier (id), a name, an ActivityType, a difficulty level, and is associated with a specific Content object. The activity also maintains a list of learning styles that it is compatible with (learningStyles). For example, a video activity may be compatible with visual learners, while a hands-on activity may be compatible with kinesthetic learners. The Activity class provides operations to deliver its content to the learner (deliverContent) and to check if it is compatible with the learner's learning style (isCompatible). This allows the system to recommend activities that are relevant and engaging for each learner, based on their individual preferences. The Activity class provides the building blocks of the learning experience, providing structured learning tasks that learners can perform to gain knowledge and skills.

Preference class: This class represents a specific preference related to a learner's learning style, allowing them to personalize their learning experience. It has a unique identifier (id), a type (PreferenceType), and a value (value). For example, a Preference object can represent a learner's preference for learning through visual aids (e.g., diagrams, videos), hearing aids (e.g., lectures, podcasts), or kinesthetic activities (e.g., hands-on projects). For the operation, getValue() retrieves the value of the preference. This would allow the system to access the preference information and use it to tailor the learning experience to the learner's individual learning style.

The Teacher Class: This class can create new activities for a specific course (createActivity), update existing activities (updateActivity), and add new courses to its list (addCourse). It can also view a specific learner's progress in a course (viewProgress), provide feedback to learners (giveFeedback), and manage learners enrolled in a specific course (manageLearners). For example, an instructor can create a new quiz activity for a specific course (createActivity), view a learner's progress in that course (viewProgress), and then provide feedback on their quiz performance (giveFeedback). The teacher plays a crucial role in guiding and supporting learners, providing instruction, feedback, and guidance to help them achieve their learning goals.

The Coursework class: This class represents a structured set of learning materials and activities that learners can enroll in to gain knowledge and skills in a specific subject area. It has a unique identifier (id), a name, a description, a level (for example, "Beginner", "Intermediate", "Advanced") and a list of activities included in the course (activities). The Course class allows you to add new activities (addActivity) and delete existing activities (remove Activity). It also provides operations to calculate a learner's average score in the course (getAverageScore), calculate a learner's completion rate in the course (getCompletionRate), and retrieve a list of activities completed by a learner in the course (getCompletedActivities). For example, an instructor can add a new activity to a course (addActivity), view a learner's average score in that course (getAverageScore), and then provide feedback on their performance based on their progress. The Courses class provides a framework for organizing and delivering learning content,

allowing learners to focus on specific areas of study and track their progress.

The Feedback class: This class represents the feedback provided to a learner by a teacher about their performance in an activity. It has a unique identifier (id), is associated with a specific performance record, and stores feedback provided by the instructor (feedback). It also keeps a list of suggested activities based on the learner's performance (suggestedActivities). The Feedback class provides an operation to generate activity suggestions based on the learner's performance (generateSuggestions). This allows the teacher to provide personalized recommendations for further learning, helping learners improve their understanding and address areas where they may need additional support.

As a summary of our proposed classroom diagram, it includes eleven interconnected classrooms, each of which plays a key role in meeting the pedagogical needs of learners, teachers, and administrators. We propose a synthesis of the main classes and their interactions:

*a) Learner-Centered Classes:*

- Learner Profile and LearningStyleProfile: Capture individual learning preferences and styles to personalize learning experiences;
- EnvironmentPreferences: Allows the configuration of specific environments adapted to sensory preferences (visual, auditory, kinesthetic);
- Performance: Tracks the learner's progress and records scores for completed activities.

*b) Content and activity classes:*

- Content: Represents multimedia learning materials;
- Activity: Defines the instructional tasks associated with the content, compatible with different learning styles;
- Course: Structures content and activities into coherent modules for learners.

*c) Interaction and feedback classes:*

- Feedback: Provides personalized feedback and suggestions to improve performance;
- Teacher: Allows teachers to create and administer courses, provide feedback, and track learners' progress.

*d) Central Class:*

- LearningEnvironment: Coordinates all interactions between classes, ensuring maximum customization and efficiency.

In conclusion, the proposed class diagram illustrates a well-defined architecture for a digital learning system, highlighting:

Personalization: With classes like LearningStyleProfile and EnvironmentPreferences, the educational experience is tailored to the specific needs of learners;

Monitoring and feedback: The system promotes scalable learning, where performance is evaluated and used to generate targeted recommendations;

Flexibility and extensibility: The use of enumerations in classes such as Content and Activity ensures that they are easy to update and maintain.

### B. The Case Diagram

In our case, the use case diagram, Fig. 2 depicts the dynamic interactions within a learning environment system, highlighting the roles of the teacher and learner.

The teacher, acting as a course creator, has the ability to design courses, develop individual activities, update existing activities, monitor the learner's progress, and provide feedback on completed tasks.

The learner, in turn, can register for courses, access and view course content, complete assigned activities, submit work for evaluation, ask the teacher for assistance, view feedback, personalize their learning experience by adjusting their preferences, and modify certain aspects of their learning environment.

The system itself plays a critical role in facilitating this interaction by recommending activities based on the learner's progress and preferences, analyzing the learning environment to identify areas for improvement, and dynamically adapting the learner's learning style based on their performance and interactivity, creating a personalized and engaging learning experience.

As a summary of our use case diagram, it models the interactions between the main actors (teachers, learners and system) within a personalized learning environment. It highlights the features and dynamic relationships needed to deliver an enriched and interactive educational experience. We mention the different roles of the main actors

*a) The teacher:*

- Content Creator and Administrator : Ability to create courses, design instructional activities, and update existing ones;
- Teacher Guide: Can monitor learners' progress, provide personalized feedback, and recommend appropriate activities.

*b) The learner:*

- Active Participant : Can view courses, complete assigned activities, and submit assignments for evaluation;
- Personalization: Can adjust learning preferences, ask for help, and view feedback to improve their experience.

*c) The system:*

- Interaction Facilitator : Recommends activities based on learners' progress and preferences;
- Dynamic Adaptation: Adjusts the learning environment and style based on learners' performance, providing continuous customization.

In conclusion, the diagram illustrates a balanced interaction architecture oriented towards personalized learning. Key features include:

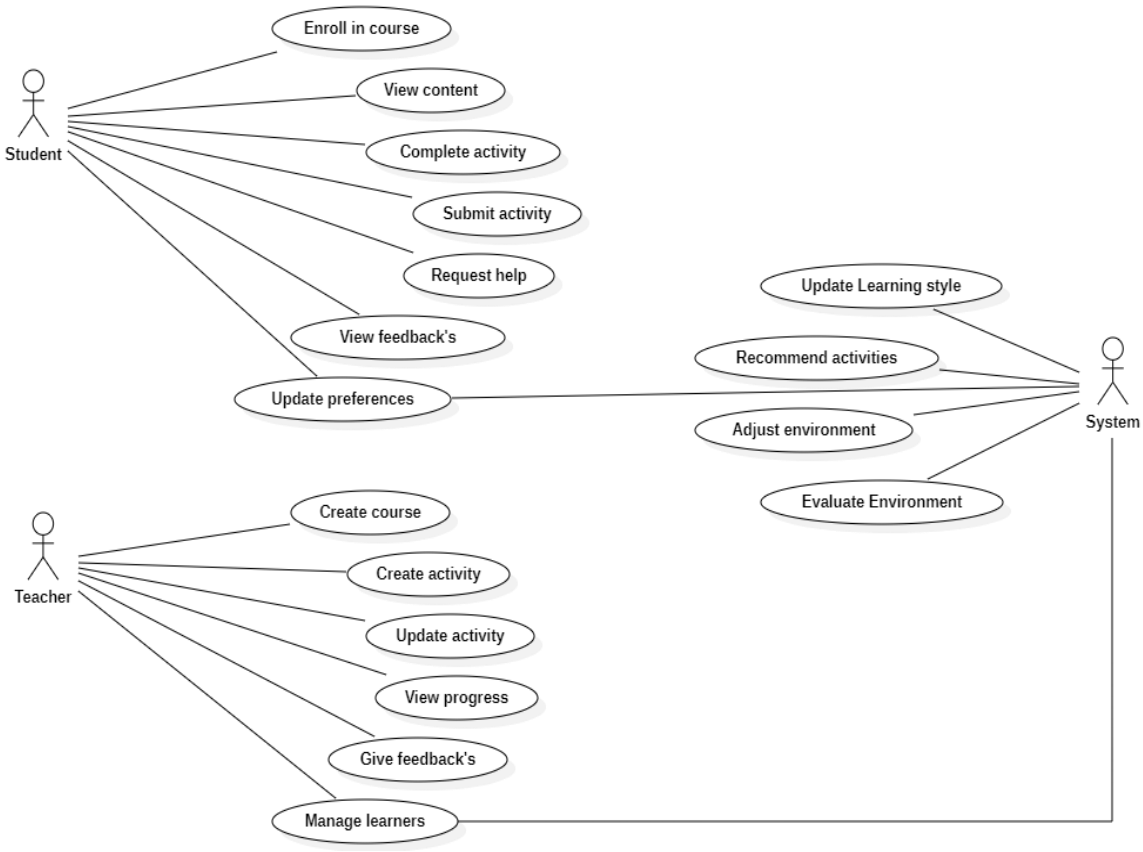


Fig. 2. Use Case Diagram.

Optimize learning with intelligent recommendations and dynamic adjustments.

Enhance learner engagement by providing an interactive and personalized experience.

Support the teacher in his or her role as a pedagogical guide with appropriate tools.

### *C. The Activity Diagram*

The Fig. 3 presents the process, which begins by retrieving the learner's learning style and preferences, which are then used to configure the learning environment according to the learner's needs. Once the environment is set up, the system provides the relevant content to the learner and recommends appropriate activities based on their learning preferences. The learner then completes the recommended activity and their performance is recorded by the system, the synchronization relationship: the "Complete Activity" and "Record Performance" activities are synchronized, which means that both must be completed before moving on to the next step where the teacher provides feedback to the learner based on their performance. Then, the system analyzes its interactions with the learning materials. Based on this analysis, the learner's learning style is updated, and the environment can be reconfigured to better meet their changing needs. The system then recommends new activities that are tailored to the learner's updated learning style and preferences, starting the cycle all over again. This iterative process ensures that the learning experience is continuously tailored to the individual needs of the learner, providing a personalized and effective learning environment.

In summary, the proposed activity diagram models a dynamic and iterative process intended to personalize learning experiences within an education system. The key steps in this process highlight the use of learner preferences and performance to continuously adapt content and activities. Key steps include:

Learning Preferences and Style Collection: The system starts by retrieving data about the learner's learning style and preferences.

Configuration of the learning environment: This data allows you to configure an environment adapted to the specific needs of the learner.

Activity recommendation: The system proposes relevant educational activities based on the preferences collected.

Performance tracking and recording: The learner's performance is recorded after each activity, allowing for objective evaluation.

Personalized feedback: The teacher provides results-based feedback, improving human-system interaction.

Interaction analysis: The system analyzes the learner's interactions with the content to adjust future recommendations.

Learning style update: Based on the data collected, the learning style is reviewed, and the environment is reconfigured to better meet the evolving needs of the learner.

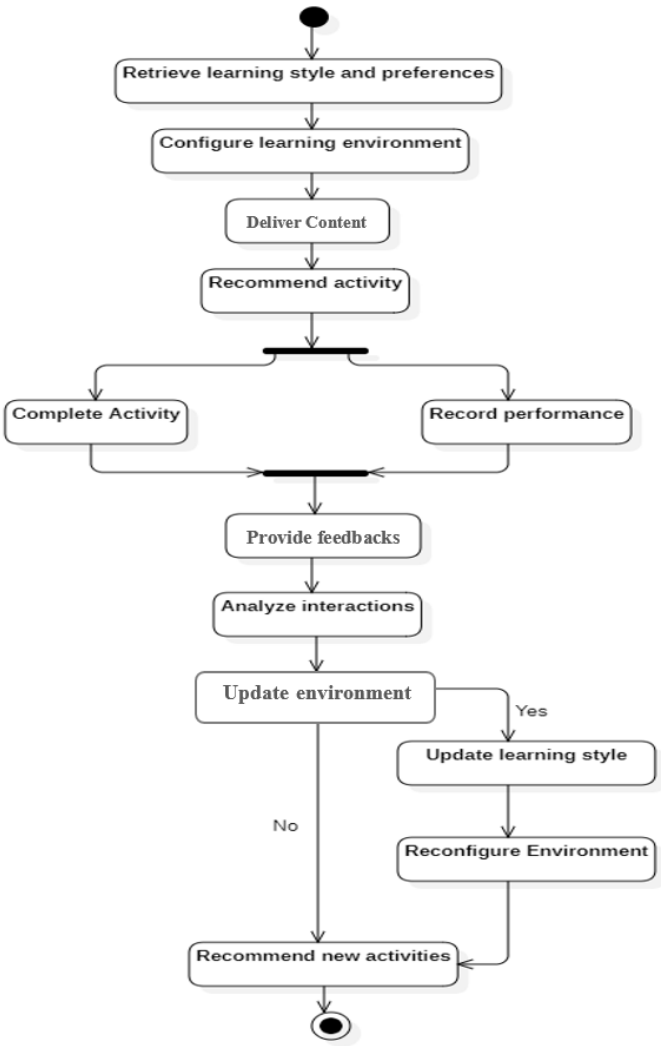


Fig. 3. Activity diagram.

This iterative process is designed to ensure continuous personalization, where each cycle improves the efficiency and relevance of the educational experience.

In conclusion, the activity diagram presented demonstrates an effective design for a personalized education system. Its strengths include:

Adaptability: Constant analysis of performance and interactions allows recommendations to be adjusted in real time.

Dynamic personalization: The iterative cycle ensures that the learning environment evolves with the needs of the learner.

The central role of the teacher: By providing qualitative feedback, the teacher plays a key role in optimizing the process.

### *D. The Sequence Diagram*

The Fig. 4 presents the sequence diagram, which illustrates the interaction between the Teacher, System, Learner, Course, Activity, Learning Environment and Performance objects.

The teacher starts by creating a new course and several activities in the system. The system stores these objects. The learner then interacts with the system, potentially accessing the course and engaging in the activities. When the learner interacts with the activities, their performance is recorded in the Performance object. The system can then analyze the learner's performance and potentially trigger an update to the learning environment, depending on the analysis. This update may involve adjustments to the learning environment or recommending new activities based on the learner's performance.

It is important to note that the teacher can also access the performance data and provide feedback to the learner through the system. This feedback can be in the form of comments, suggestions, or advice.

The diagram highlights the collaborative nature of the learning environment, where the teacher creates and manages the content, the learner interacts with the system, and the system dynamically adapts to the learner's progress and needs, with the teacher providing feedback to improve the learning process.

In summary, the sequence diagram provided highlights the dynamic interactions between the key actors and components of an education system, such as the teacher, the learner, the system, the courses, the activities, and the learning environment. This model illustrates a collaborative process:

Role of the teacher: Creation of educational content and consultation of learners' performance data.

Learner role: Interaction with the system through the proposed activities, generating performance data.

System management: Data recording, performance analysis, dynamic adaptation of the learning environment, recommendation and new activities.

Personalized adaptation: Adjustments made to the learning environment based on learners' performance, enhancing pedagogical effectiveness.

The model also emphasizes the importance of feedback from teaching, stopping learning through guidance and complementary adjustments.

In conclusion, this sequence diagram illustrates an interactive educational and adaptive ecosystem, where the teaching, the learner, and the ecosystem system for the goals of the goals optimized. With a focus on personalization and dynamic feedback, it demonstrates how an environment of environment designed within the framework of individual learners' needs while maintaining an active role for teaching.

This modeled approach is particularly relevant in contexts where digital learning requires flexibility, responsiveness and collaboration to deliver a rich and engaging experience.

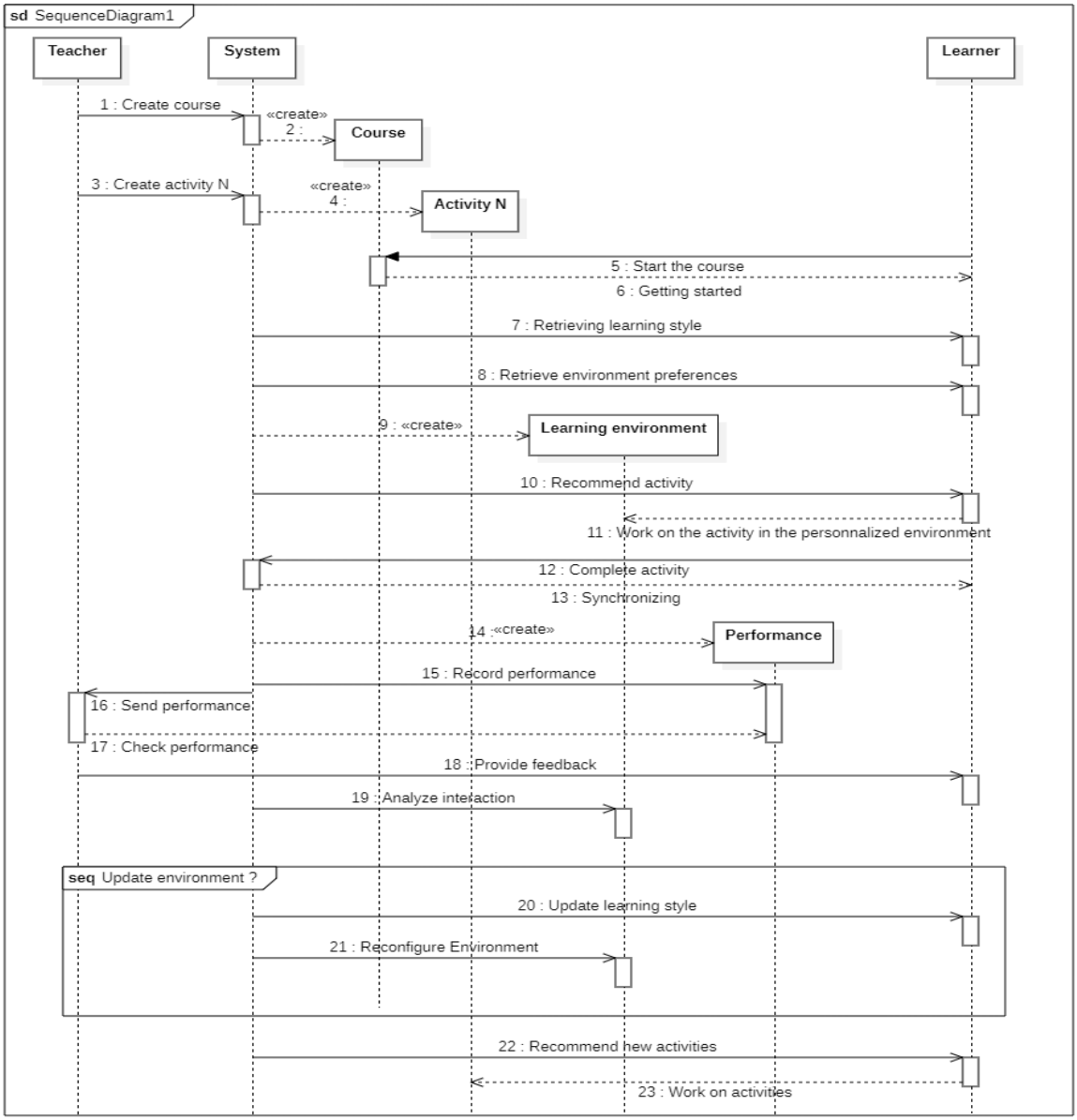


Fig. 4. Sequence Diagram.

## V. Theoretical and Practical Contributions

This research makes three main contributions to the field of adaptive hypermedia systems. On a theoretical level, it proposes an innovative conceptual model that unifies content and user interface adaptation, thus filling a gap identified in the literature [57]. The developed UML modeling framework offers a more comprehensive formalization than existing architectures [58], explicitly integrating dynamic decision-making and contextual adjustment mechanisms. From a methodological perspective, our approach demonstrates how modeling techniques can be combined with AI algorithms to create more responsive and personalized learning systems. On a practical level, this work offers concrete benefits for various stakeholders in the educational field. For learners, the system offers a more engaging experience better adapted to their individual needs, which could improve retention and success rates. For instructional designers, our model provides a structured framework for developing adaptive content without requiring advanced technical skills. Educational institutions will find a scalable solution that can be gradually integrated into their existing infrastructures, with potential implications in terms of cost reduction and optimization of educational resources.

## VI. Research Limitations

Several limitations deserve to be highlighted in this study. First, the current model relies on assumptions regarding the availability and quality of training data, which may not always be verified in real-world educational contexts. Second, although our UML approach allows for a comprehensive representation of the system, its practical implementation would require computational resources that could pose challenges in some capacity-limited environments. Another important limitation concerns the generalizability of the results: our preliminary

validation, while promising, was conducted in a specific context and should be extended to more diverse learner populations. Finally, the current system does not yet fully address aspects related to interoperability with other learning platforms, a crucial dimension for widespread adoption. However, these limitations open up interesting avenues for future research, particularly on the optimization of adaptation algorithms and integration with existing educational standards.

## VII. Suggestions for Future Research

Although the technologies and architectures of adaptive systems have evolved enormously, several challenges remain:

*1)* Next, we will develop the prototyping of the system based on the diagrams developed in this study, and ultimately develop our hypermedia system.

*2)* Current adaptive systems often use AI models, which limits teachers' and learners' confidence in the proposed recommendations. We can then develop explainability mechanisms (XAI) integrated into UML diagrams (annotations in sequence diagrams to trace adaptation decisions).

*3)* Current profiles often ignore emotional states (frustration, motivation), which are critical in pedagogy. We can therefore extend the class diagram with emotional attributes (biometric data or textual analyses).

## VIII. Conclusion

Adaptive learning systems represent a major advancement in digital pedagogy, drawing on a synergy between artificial intelligence, data analytics, and cloud infrastructures. These technologies enable the delivery of truly personalized experiences, where every element—content, pace, assessment methods, and interface—dynamically adjusts to the learner's needs. Modern microservice architectures offer the flexibility to continually integrate new capabilities, such as emotion analysis or augmented reality, while ensuring performance and security. However, this potential comes with crucial challenges: algorithm transparency, energy footprint reduction, and sensitive data protection. The future of these systems lies in their ability to combine technological sophistication with a human-centered approach, while adhering to open standards for widespread adoption. The next frontier will be developing predictive and immersive learning ecosystems that can not only adapt to learners, but also anticipate their needs throughout their educational journey.

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# From Code Analysis to Fault Localization: A Survey of Graph Neural Network Applications in Software Engineering

Maojie PAN*, Shengxu LIN, Zhenghong XIAO
School of Computer Science, Guangdong Polytechnic Normal University, Guangzhou, Guangdong 510665, China

***Abstract*—Graph Neural Networks (GNNs) represent a class of deep machine learning algorithms for analyzing or processing data in graph structure. Most software development activities, such as fault localization, code analysis, and measures of software quality, are inherently graph-like. This survey assesses GNN applications in different subfields of software engineering with special attention to defect identification and other quality assurance processes. A summary of the current state-of-the-art is presented, highlighting important advances in GNN methodologies and their application in software engineering. Further, the factors that limit the current solutions in terms of their use for a wider range of tasks are also considered, including scalability, interpretability, and compatibility with other tools. Some suggestions for future work are presented, including the enhancement of new architectures of GNNs, the enhancement of the interpretability of GNNs, and the design of a large-scale dataset of GNNs. The survey will, therefore, provide detailed insight into how the application of GNNs offers the possibility of enhancing software development processes and the quality of the final product.**

***Keywords*—Graph neural networks; fault localization; code analysis; software quality***

## I. Introduction

### A. Context

Graph Neural Networks (GNNs) form branches of neural networks that generate inferences from data in a graph form. These graphs comprise nodes and edges and facilitate comprehension of intricate data dependencies and connections [1]. GNNs have recently proven to be effective in several real-world applications, including social networks, chemistry, and natural language processing [2]. Because of these characteristics, deep graphs can be applied to modeling and learning structures with complex interdependencies between them [3].

In software development, a lot of processes are inherently associated with data that can be naturally modeled using graphs. These include control flow diagrams, dependency diagrams, and an abstract syntax tree where software programs' structure and relationships are analyzed [4]. These representations are rather complex, and the traditional paradigm of machine learning often fails to identify all the necessary features and relationships within the graphs, which leads to poor results in fault localization, code analysis, and software quality evaluation [5]. However, the appearance of GNNs provides a more suitable opportunity to explore the areas of modern software development, as they can make use of the structural information encoded in these diagrams [6].

### B. Motivation

Fault location, a key component of software debugging and maintenance, is one area where GNNs have shown considerable promise [7]. Through program graphs, where programs are modeled, GNNs can identify patterns related to faulty code snippets, guiding developers to locate the precise location of the bug more effectively [8]. Similarly, GNNs can be used in code analysis for functions including code synthesis, clone detection, and refactoring by understanding the structural similarities and differences between code segments. These capabilities can significantly reduce the time and effort required to maintain and improve software systems [9].

In addition to fault location and code analysis, software quality assurance also utilizes GNNs to prioritize test cases by identifying the potential effects of each test case on the software, to predict error-prone regions based on historical data, and to enhance the overall reliability of software systems [10]. Developing applications with the help of GNNs is not without challenges, although. Scalability, interpretability, data availability, and integration with existing tools are some of the areas that need to be addressed to leverage the benefits of GNNs in this field fully.

### C. Problem Statement

Despite recent growth in the adoption of GNNs in software development, there remains a lack of complete knowledge about their proper usage within various software development processes, such as fault localization, code analysis, and quality assurance. Some of the unanswered questions include the scalability issues of GNNs, the interpretability of the results, and the integration of GNNs with traditional software tools.

### D. Research Objectives

The paper provides an exhaustive survey of recent advancements, outlines the various applications of GNNs in software development, and presents challenges and directions for this emerging field. Applications of GNNs to fault localization, code analysis, and quality assurance will be discussed, and the methods and results will be assessed. We will also analyze the practical issues faced by researchers, including those related to scalability, the need for easy-to-understand models, and the integration of GNNs with current software development tools and processes. This survey aims to identify the revolutionary promise of GNNs in software development

and to encourage more research and development in this field. The research attempts to answer the following research questions.

- What are the current applications of GNNs to essential software engineering activities like fault detection and code analysis?
- What are the comparative advantages of GNN-based approaches over traditional static and dynamic analyses?
- What are the limitations and challenges of deploying GNNs at scale in real-world software development processes?
- What are hybrid approaches that integrate classic methods with GNNs?

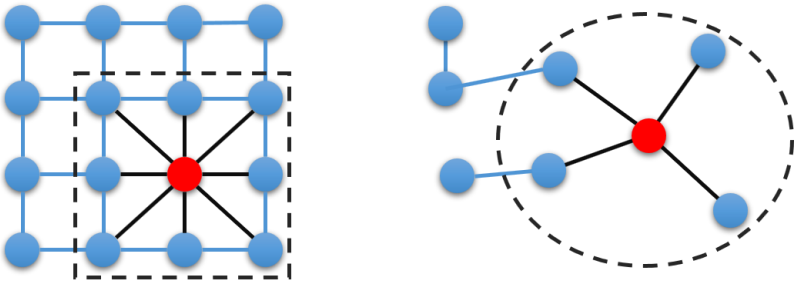
The paper is organized as follows. In Section II, a general overview of GNNs and their fundamental concepts and essential techniques is presented. In Section III, the targeted applications of GNNs in software development are presented, and their influence on fault localization, code analysis, and quality assurance is highlighted. In Section IV, directions and potential advancements are explored, and contemporary challenges to applying GNNs to software development are discussed. The paper concludes with a general discussion of its findings and contributions in Section V.

## II. Graph Neural Networks: An Overview

### A. Definition and Background

GNNs are a class of neural networks designed to perform inference on data represented as graphs. A graph G is defined as $G = (V, E)$, where $V$ is a set of vertices (or nodes) and $E$ is a set of edges connecting the nodes. Each node $v \in V$ and edge $e \in E$ can have associated features, which are essential for capturing the properties and relationships within the data.

GNNs are inspired by Convolutional Neural Networks (CNNs). Before delving into GNNs, it is essential to understand why CNNs and Recurrent Neural Networks (RNNs) cannot handle graph data effectively. As depicted in Fig. 1, CNNs operate on data with a grid structure, such as images. As an alternative, RNNs are adapted to sequences, like text.



2-D Convolution neural network  Graph neural network

Fig. 1. CNN vs. GNN.

Text data is usually stored within arrays. Similarly, matrices are optimal to store image data. But, as also depicted in Fig. 1, arrays and matrices are incapable of handling graph data. Graphs employ a special process called graph convolution. This technique enables deep neural networks to process graph-structured data and yield a GNN directly. It can be seen that masking techniques and filtering operations are employed to convert images to vectors. However, classical masking techniques are not suitable for graph data input, as depicted in the rightmost image.

In contrast to classical static and dynamic analyses that act based on pre-declared rules or symbolic rationale, GNNs use data-driven learning to extract patterns from graph-structured program representations. This learning feature enables GNNs to generalize across codebases, identify patterns that are not easily specified by human-created rules, and evolve to respond to new domains without requiring human intervention. Some static analyses incorporate feedback loops (e.g., via CEGAR) but fail to include the ongoing, end-to-end learning process that allows GNNs to fine-tune with additional data.

### B. GNN Evolution

Significant development has occurred in applying neural networks to graph-structured data over the years. Early approaches, like the use of recursive neural networks, laid the foundation by leveraging the same set of parameters repeatedly over the graph structure [11]. Nonetheless, this was limited by the fact that the approaches were unable to efficiently adopt arbitrary graph structures.

The advent of Graph Convolutional Networks (GCNs) was a groundbreaking development. GCNs generalize the concept of convolution to graph-structured data, rather than grid-like data (like images). By operationalizing convolution over the neighborhood of every node, GCNs are especially useful for node classification and link prediction tasks [12]. Following the success of GCNs, several different classes of GNNs have emerged:

- Graph Attention Networks (GATs): These networks utilize an attention mechanism that weighs the importance of various node features [13]. This will enable the model to emphasize the most significant components of the graph and improve performance in cases where some nodes have greater influence.
- Graph Recurrent Networks (GRNs): Utilize recurrent network architectures to process graph data. Such networks are ideally suited to sequential graph data, where the ordering of the node or edge is considered significant [14].

- Graph Autoencoders (GAEs): Used in unsupervised learning from graph data. GAEs encode graph data into a latent space and reconstruct the graph, finding applications in graph generation and detecting anomalies [15].

### C. GNN Training

Training a GNN involves learning parameters to identify patterns and relationships within the graph data. Training can be supervised, unsupervised, or semi-supervised based on the availability of labeled data.

- Supervised learning: Trains the GNN based on labeled graph data, and the labels are associated with the node, edge, or graph level [16]. The model is trained to make predictions of labels based on input features and graph topology.
- Unsupervised learning: The GNN is trained to embed the graph data without labels. Techniques such as graph autoencoders and contrastive learning are typically employed to obtain informative representations of the graph [17].
- Semi-supervised learning: It combines labeled and unlabeled data to improve the learning process [18]. In cases where labeled data is limited, and many real-world applications face this issue, this is especially helpful.

## III. GNN Applications in Software Engineering

GNNs have become a universal tool in software development, leveraging the inherent graph-like characteristics of a wide variety of software artifacts. As shown in Table I, various GNN architectures possess distinct strengths and applications, making them suitable for a wide range of software development activities. Varying from code analysis and fault location to software quality assurance, numerous paths can be modeled, analyzed, and optimized using GNNs to enhance software systems. This section focuses on the application of GNNs in software development, with a particular emphasis on the various architectures employed to address complex issues and enhance the effectiveness and efficiency of software development.

TABLE I. Summary of GNN Architectures

| GNN architecture | Key features | Strengths | Typical applications in software engineering |
|---|---|---|---|
| GCN | Applies convolution operations to graph data and aggregates information from neighboring nodes. | Efficient in collecting local neighborhood information. | Node classification, fault localization, code analysis. |
| GAT | Utilizes attention mechanisms to weigh the importance of neighboring nodes' features. | Allows the model to focus on the most relevant parts of the graph. | Code summarization, bug prediction, and test case prioritization. |
| GRN | Incorporates recurrent neural network architectures for processing graph data over time. | Effective for sequential graph data, capturing temporal dependencies. | Analyzing execution traces, dynamic analysis. |
| GAE | Encodes graph structures into a latent space and reconstructs the graph for unsupervised learning. | Useful for graph generation and anomaly detection. | Detecting code clones unsupervised code analysis. |
| Message Passing Neural Network (MPNN) | Generalizes GNNs with a message passing framework where nodes iteratively exchange messages. | Flexible in handling different types of graph structures and tasks. | Program dependency analysis bug prediction. |
| Spatial-Temporal GNN (ST-GNN) | Models both spatial and temporal aspects of graph data, handling dynamic changes in the graph. | Captures both structural and temporal evolution of graphs. | Real-time monitoring of software systems and dynamic code analysis. |

### A. Fault Localization

Fault location is a critical part of software maintenance and debugging, aiming to identify the precise fault locations within a software program [19]. Fault location strategies are typically based on static or dynamic analysis techniques, which can be time-consuming and may not always yield accurate results. The capability of modeling and learning with graph-structured data offers a promising solution for enhancing fault location by leveraging the intrinsic software program structure. As demonstrated in geotechnical engineering, domain-specific modeling in the field of geotechnical engineering [20] shows that adapting models to consider material heterogeneity and structural anisotropy enhances prediction capability. Similarly, task-specific tuning of the GNN architecture may be necessary for code analysis and fault localization.

Trained static analysis approaches, such as data flow analysis, control flow analysis, and abstraction-based analysis, have long supported software fault detection and code understanding. However, they are typically based on predefined rules and cannot handle dynamic software behaviors or loosely formatted source code. By contrast, GNN-based analysis learns to operate directly from the graph structure of code and execution traces. This can guide the model to detect subtle, non-local relations and semantic structures that are not detectable with earlier analyses. Additionally, various program representations, such as Abstract Syntax Trees (ASTs), Program Dependency Graphs (PDGs), and runtime traces, can be combined by GNNs within a single learning framework, providing a richer and more dynamic understanding of software systems.

*1) Program dependency graphs:* PDGs are a popular format adopted in fault localization [21]. PDGs encode the interdependencies between various components of a program, in the form of data dependencies (which variables depend on) and control dependencies (which statements cause others to execute). In encoding a program in a PDG, GNNs can examine the interrelations between various facets of the code.

The GNNs can be trained with the PDGs to identify patterns related to defective code snippets. For example, a GNN can be trained to identify nodes within the PDG that are likely to have faults by learning from historical fault data. This requires

encoding node and edge features within the PDG and applying a message-passing function to consolidate information passed by the neighboring nodes. The node representations generated can be used to make predictions about the presence of a fault at each node.

*2) Abstract syntax trees:* ASTs embody the program's syntax structure. Each node within an AST denotes a construct in the source code, e.g., a variable, an operator, or a control-flow statement [22]. ASTs give a hierarchical representation of a program, reflecting the nested relationships between program components.

ASTs are amenable to GNN applications that aid in fault localization by leveraging code semantics and structure. By applying GNNs to processed ASTs, faults can be identified based on syntactic patterns, effectively learning to recognize error-prone code patterns or patterns or combinations of patterns. This can be especially useful for identifying faults that result from intricate relationships between various code components.

GNNs capture and leverage the hierarchies and control flows embedded in code, such as nested loops, conditional statements, and recursion. Such patterns of code are common to frequent bugs, including infinite loops, misbounds in loops (i.e., off-by-one errors), faulty exception handling, and misuse of break and continue statements. Through examination of ASTs and control flow graphs, GNNs can identify recurring structural patterns that relate to such bugs. For instance, GNNs can identify anomalies in nesting within loops that suggest missing base cases or faulty exit conditions within recursive routines, enabling early detection of runtime faults and logical errors.

*3) Dynamic analysis with execution traces:* Most software defects have their roots in faulty state initialization or incorrect state transitions, and not all of them are explicitly programmed in the static code structure [23]. To overcome this, execution traces, runtime event representations in graph format, can be fed to GNNs to capture variable updates, function call sequences, and conditional jumps. Traces embed time-dependent relationships and implicit transitions between states, enabling GNNs to capture patterns related to erroneous program execution. In cases where more implicit information is lacking, hybrid GNNs can take both static data (e.g., ASTs or PDGs) and dynamic data (e.g., memory dumps, execution traces) to create a more holistic fault detection system.

*4) Empirical studies and results:* Numerous empirical studies have demonstrated the effectiveness of GNNs in fault localization. The investigations typically involve training the GNNs with known faulty programs and subsequently with unknown programs. Precision, F1-score, and recall are metrics used to measure a model's capability to identify faulty portions of code correctly.

For instance, one experiment may involve training a GNN using a database of Java programs based on their PDGs and ASTs to make predictions about fault locations. The outcome can demonstrate that a GNN outperforms conventional fault localization methods, such as SBFL, by yielding more accurate and precise fault predictions. Such experiments highlight the tremendous potential of GNNs to enhance the efficiency and efficacy of fault localization processes within software development.

Fig. 2 illustrates a novel fault-localization technique that utilizes a graph-based representation of faulty feeders. Fault detection accuracy is improved by integrating data from different data sources, like geographic information system (GIS) databases and supervisory control and data acquisition (SCADA) systems. GIS databases provide important information about network topology, protection device locations, and electrical characteristics. SCADA systems provide real-time operational data such as protection device activations, fault currents and voltage measurements. To further increase the intelligence of the system, data from customer information systems (CIS) and station oscillographs can be integrated.

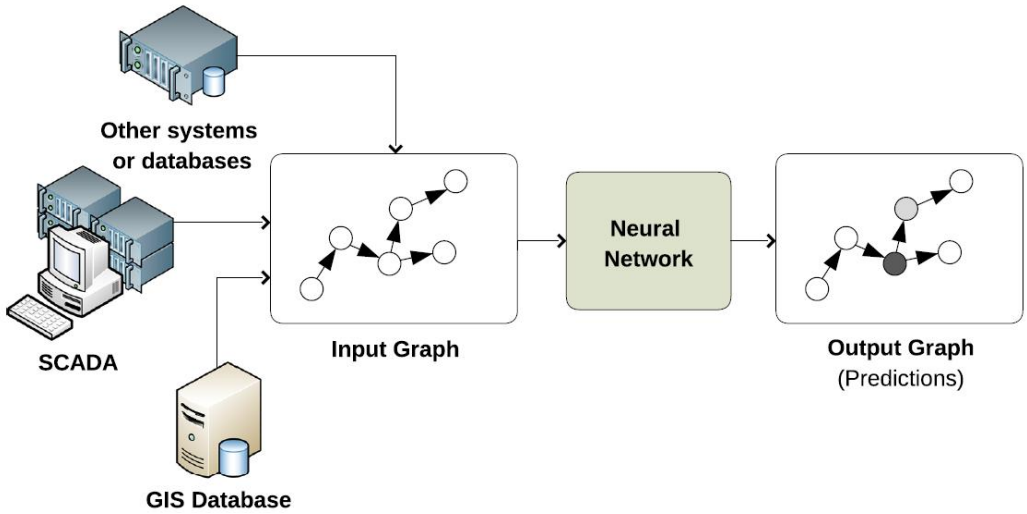



Fig. 2. A novel fault localization technique using graph-based representation.

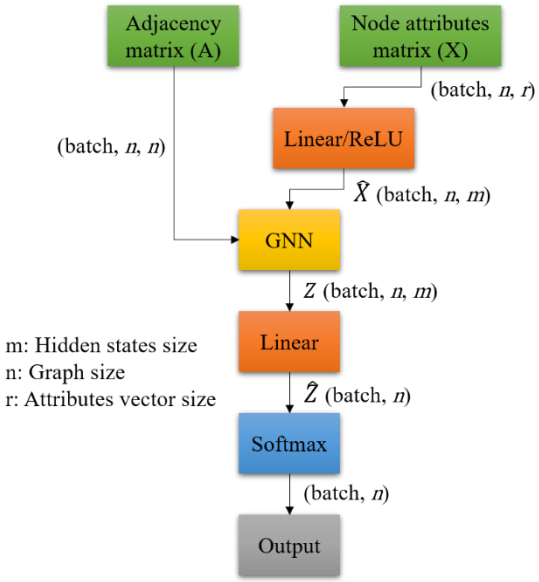



Fig. 3. Neural network model processing graph.

The graph-based representation is then fed to a neural network model, as shown in Fig. 3. The input to this model is the adjacency matrix A and the attribute matrix X of the graph. The first stage employs a linear combination with a rectified linear unit (ReLU) activation function, which projects the input features into a new space of representations. The size of the hidden states and the number of input attributes are hyperparameters that influence the model's capacity and generalization capability.

$$\hat{X} = ReLU(W_{in}X + b_{in}) \quad (1)$$

In the subsequent layers, a GNN is employed to extract the dense relationships between the nodes in the graph. A GNN propagates information over the graph sequentially, allowing the model to capture relationships between non-immediately adjacent nodes. The number of propagation steps is a hyperparameter that controls how much the model supports long-term dependencies. But more steps of propagation correspond to increased computational cost and memory demand.

The network computes a score for every node via a linear combination and passes this to a softmax function, where the scores are normalized to a probability distribution. This is to calculate the probability that a node is the location of the fault.

### B. Code Analysis

Code analysis involves a set of activities to comprehend and enhance the quality of software [24]. Some of the activities involved include code summarization, clone detection, and refactoring, among others. Given that GNNs can capture the structural and relational aspects of code, they provide substantial benefits in accomplishing the above activities by generating more precise and informative findings compared to the conventional methods.

*1) Code summarization:* Code summarization necessitates the creation of compact, natural language descriptions of code functionality [25]. This is a fundamental requirement of documentation and codebase browsing over large and intricate codebases. GNNs can leverage the structural information contained in ASTs and other code graphs to enhance code summarization.

By representing code in a graph format, GNNs can capture the structural and relational information that is crucial to the functionality of code snippets. As a case in point, a GNN can be trained to embed the AST of a code snippet and create a summary by translating the learned representation back into natural language. This enables the model to comprehend the relationships and contexts within the code, providing more accurate and relevant summaries.

*2) Clone detection:* Code clone detection aims to identify similar or duplicated code sequences within a codebase. Clones are a source of maintenance issues and potential errors and are therefore especially essential to detect for software quality [26]. Clone detection can be greatly aided by the use of GNNs that focus on structural similarities in the graph representations of code.

Clone detection can be performed by representing code snippets as graphs (e.g., PDGs, ASTs) and applying GNNs to extract their structural representations. A comparison of the structural representations will enable the identification of similar code fragments, despite their syntactic differences. This feature is especially helpful in Type-3 clone detection, where the code snippets are syntactically different but semantically the same.

*3) Code refactoring:* Code refactoring rearranges previously written code without altering its external functionality, making the code more readable, maintainable, and efficient [27]. Identifying refactoring areas and recommending suitable transformations are the two fundamental challenges of refactoring. GNNs can help refactoring by inspecting the code structure and extracting patterns that suggest that refactoring is warranted.

The GNNs are trained over refactoring histories and can detect code smells and anti-patterns that are usually amenable to refactoring. By encoding code graphs and applying a GNN to operate over them, the models can suggest refactoring opportunities based on the detected patterns. A GNN, for instance, will detect duplicated code, long sequences of methods, or highly coupled classes that are amenable to refactoring. The employment of GNNs in code refactoring has made refactoring proposals more accurate and beneficial. Developers employ such models to automate refactoring suggestions and provide optimal recommendations.

*4) Empirical studies and results:* Empirical studies on applying GNNs to code analysis issues have demonstrated their effectiveness and superiority over traditional alternatives. For example, studies on code summarization using GNN-based methods have demonstrated improved performance in generating accurate and concise descriptions of code. Likewise, studies on clone detection have demonstrated that clones can be

effectively identified by GNNs, yielding increased precision and recall compared to traditional methods.

Empirical studies of code refactoring have demonstrated the capability of GNNs to identify sophisticated code smells and provide useful refactoring suggestions. The studies are carried out with benchmark data sets and actual codebases and yield evidence of the utility of GNNs in code analysis.

Fig. 4 shows a hybrid GNN framework for code analysis. This framework integrates both static and dynamic graph representations to improve code summary learning. It consists of four main components: (1) Retrieval-Augmented Static Graph Construction, which augments the original code graph with retrieved code summary pairs to improve feature learning; (2) Attention-based dynamic graph construction, where a global attention mechanism enables message propagation between arbitrary pairs of nodes, enabling more flexible relationships; (3) Hybrid GNN (HGNN), which combines information from static and dynamic graphs through hybrid messaging to enrich node representations; and (4) Decoder, which uses an attention-based LSTM model to generate a code summary from the learned representations. This framework effectively leverages both structural and dynamic aspects of code to improve the quality of code analysis and summarization tasks.

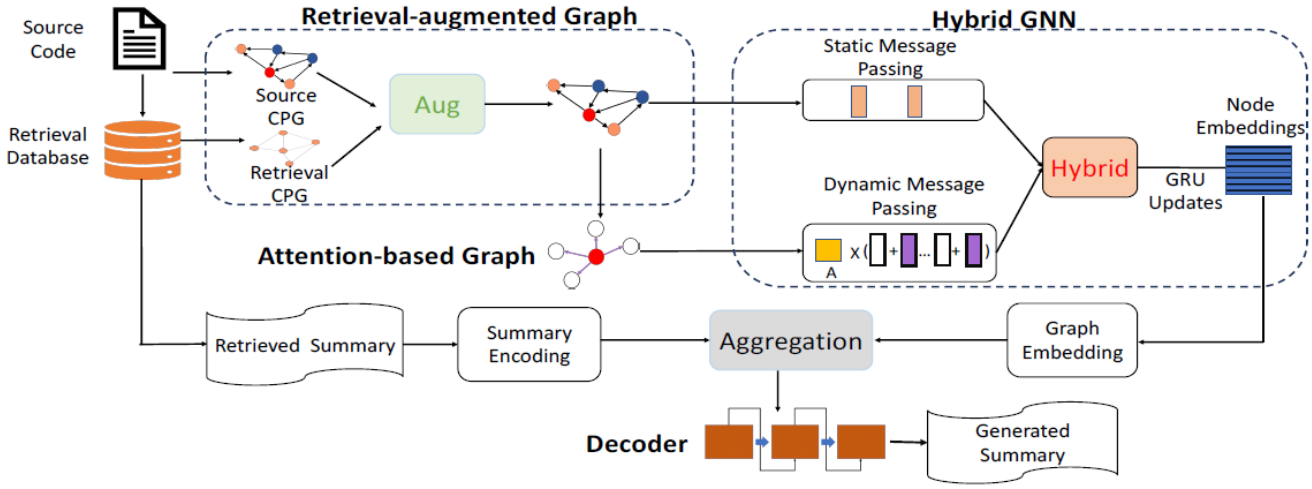



Fig. 4. Hybrid GNN framework for code analysis.

### C. Software Quality Assurance

Software Quality Assurance (SQA) is an essential software engineering process that ensures software artifacts meet the quality standards expected of them [28]. This includes activities that are related to testing, verification, validation, and bug prediction. GNNs have demonstrated tremendous potential to improve many aspects of SQA by extracting structural information embedded in software artefacts to make more accurate predictions and provide better insights.

*1) Test case prioritization:* Test case prioritization involves sequencing test cases in a way that prioritized test cases are run first [29]. This becomes more significant with regression testing, where a full test suite must be rerun, and for that, there are time and cost factors. Sorting test cases can be facilitated with the help of GNNs by identifying the relationships and dependencies within the software.

By representing the software and test cases as a graph, where code components serve as nodes and dependencies or interactions are represented as edges, the areas of the software most likely to be affected by recent updates can be identified using GNNs. This helps the model concentrate only on test cases that correspond to the key areas. Experimental studies have demonstrated that test case prioritization with the aid of GNNs can facilitate fault detection much earlier, thereby enhancing the efficiency and effectiveness of the test process.

*2) Bug prediction:* Bug prediction entails predicting where and when defects are likely to occur in various areas of the software. Proper bug prediction can be useful in better allocating resources and targeting quality assurance activities to the areas of the code that are at the highest risk of defects [30]. Bug prediction can be significantly improved by utilizing GNNs that analyze the structural characteristics of software and learn from bug data over time.

Software can be modeled using different types of graphs, such as dependency graphs or co-change graphs, where nodes and dependencies, or co-change relations, represent software components, and edges represent these relationships. GNNs can process such graphs to identify patterns that predict bug-prone locations. For instance, a GNN can be trained using past data to make predictions about the likelihood of defects in various components based on their structural characteristics and change history. Experiments have established that bug prediction models based upon GNNs are more precise and detailed compared to conventional statistical and machine-learning-based models.

*3) Code review assistance:* Code reviews are an essential aspect of the software development life cycle, ensuring improvement in code quality through peer review. GNNs can be leveraged to assist with code reviews by suggesting and detecting potential issues, as well as recommending enhancements [31]. Based on analyzing the code structure and

the relationships between various code components, GNNs can identify problematic areas.

For example, code smells, security issues, or compliance with the coding standard can be detected by GNNs. By treating the code and its dependencies as a graph data type and learning patterns typical of high-quality code, GNNs can provide developers with real-time feedback during code reviews. This not only accelerates the review process but also helps ensure a superior level of code quality.

*4) Empirical studies and results:* Empirical research on applying the use of GNNs in software quality assurance has produced promising evidence. In test case prioritization, research has shown that GNNs are capable of achieving better fault detection at earlier stages of the test process than other prioritization techniques. In bug prediction, research has shown that predictions made by GNNs are more accurate, enabling teams to address issues proactively.

While helping with code review, we have observed that systems utilizing GNNs enhance review efficiency and effectiveness by identifying a higher percentage of issues without manual examination. Such research involves real-world data sets and compares them with standard practices to validate the benefits gained from applying GNNs.

## IV. Future Directions

The application of GNNs in software engineering is still in its early stages, with numerous areas to explore and develop in the future. With the improvement and development of GNNs, their capability to revolutionize various facets of software engineering, including fault localization, code analysis, and software quality assurance, becomes increasingly evident. Table II outlines some of the key areas to explore and refine in the future, providing a systematic overview of the essential directions that will drive the continued improvement and deployment of GNNs within this discipline.

TABLE II. Key Areas for Future Research and Development in GNNs for Software Engineering

| Future direction | Description | Expected outcomes |
|---|---|---|
| Advanced GNN architectures | Development of more specialized and scalable GNN architectures to handle large-scale, complex software systems. | Improved efficiency and effectiveness in handling vast data and intricate relationships. |
| Explainable AI for GNNs | Creation of methods to enhance the interpretability and transparency of GNN models. | Increased trust and adoption of GNNs through clearer, more understandable predictions. |
| Real-world applications | Conducting empirical studies and applying GNNs in real-world software projects. | Validation of GNN effectiveness, identification of strengths and weaknesses, and wider industry adoption. |
| Integration with development tools | Seamless integration of GNNs into IDEs and CI/CD pipelines. | Enhanced real-time analysis, automated testing, and proactive bug detection. |
| Large-scale and high-quality datasets | Creation of comprehensive and publicly available datasets for GNN training and evaluation. | Improved performance of GNN models through access to diverse, well-annotated datasets. |
| Cross-disciplinary research | Encouraging collaboration across computer science, network science, cognitive science, and other disciplines. | Innovative solutions, improved scalability, and interpretability of GNNs in software engineering. |

### A. Advanced GNN Architectures

To fully realize the potential of GNNs in software development, more advanced and specialized architectures of GNNs need to be designed. Currently, architectures such as GCNs and GATs show promise but also face limitations when dealing with large and complex software systems. In their next steps, researchers should strive to develop scalable architectures of GNNs that can meaningfully interact with the vast amounts of data and intricate relationships found in large software projects.

Moreover, hybrid approaches that integrate GNNs with additional machine learning methods or domain-specific knowledge could further enhance their effectiveness. For example, integrating NLP methods with GNNs could enhance code documentation and abstraction. Additionally, integrating standard static and dynamic analysis tools with GNNs could result in more accurate fault localization and bug prediction.

### B. Explainable AI for GNNs

One of the biggest hindrances to the large-scale adoption of GNNs in software development is the interpretability of their outputs. Developers and stakeholders should be able to know the rationale behind the predictions and suggestions made by the GNN models. As a result, there is a vital need to develop explainable AI methods for GNNs.

Research in this area should aim to develop methods that yield transparent and comprehensible explanations of the predictions made by a GNN. Mechanisms such as attention, feature importance analysis, and visualization tools can be designed to ensure that GNNs are more transparent and their output is more interpretable. As the explainability of GNN models improves, developers are more likely to have confidence in and efficiently utilize them in their development process.

### C. Real-world Applications

To demonstrate the utility of GNNs in software development, it is necessary to conduct extensive empirical research and evaluate GNN models against real-world software projects. Such research should be conducted using different datasets and programming languages, as well as various development platforms and software fields. By comparing GNN models with conventional methods and measuring their efficiency in actual cases, the strengths and limitations can be identified, allowing for targeted areas for improvement.

Collaborating with industrial partners to implement GNNs in real-world applications can yield valuable insights and feedback. Industry case studies that demonstrate successful GNN implementation also have the potential to present practical applications and promote broader adoption.

### D. Integration with Development Tools

For GNNs to be successfully employed in software development, they must be integrated seamlessly into existing development tools and processes. This includes developing usable interfaces, plugins, and APIs that enable developers to integrate GNN-based recommendations and analysis into their everyday workflows.

Future efforts should be directed toward building Integrated Development Environments (IDEs) and Continuous Integration/Continuous Deployment (CI/CD) pipelines that leverage the power of GNNs. This integration would enable real-time analysis, automated testing, and early bug detection, resulting in a more efficient and higher-quality software development process.

Outside of single-use cases, GNNs have the potential to extend to pre-existing analyses by delivering rich semantic outputs, such as code representations from summarization or similarity measures in clone detection. Those representations can be incorporated into symbolic or data-flow analysis to enhance inference procedures. Semantic embedding, for instance, can be used as a feature input in path prioritization during symbolic execution. Code clone clusters can be utilized to facilitate property propagation in verification. This inter-model synergy presents a hybridized strategy that blends the accuracy of conventional tools with the adaptability and abstraction power of deep learning algorithms.

### E. Large-Scale and High-Quality Datasets

The effectiveness of GNN models is highly dependent upon having large, high-quality datasets to train and test them. Software engineering makes the development of such datasets problematic due to the heterogeneity of software projects and the necessity of accurate annotations. Future research should be directed toward developing well-rounded and public datasets that span a large gamut of software engineering activities.

Joint initiatives between academia, industry, and open-source projects can curate and pool valuable datasets. Such datasets should comprise different representations of graphs, such as program dependency graphs, execution traces, abstract syntax trees, and labeled data to perform activities like bug prediction, code summarization, and fault localization.

### F. Cross-Disciplinary Research

Software engineering is a multidisciplinary field that combines components of computer science, mathematics, and engineering. Increased cross-disciplinary research will be encouraged in the future to harness the power of GNNs in software engineering. Concepts and methods borrowed from network science, data mining, and cognitive science can offer new insights and approaches to enhance GNN applications.

Joint research endeavors have the potential to provide innovative solutions to intricate problems in software development. For example, concepts borrowed from cognitive science enhance the usability and interpretation of GNN models, while innovations in network science facilitate the design of more scalable and efficient GNN architectures.

## V. Conclusion

This research highlighted the significant potential of GNNs for revolutionizing software engineering, particularly fault localization, code analysis, and software quality assurance. With the capability to tap into the graph-structured information of software data, GNNs provide better insights and more precise predictions than classical alternatives. Our survey identified the current applications of GNNs to software issues in areas of interest, outlined key research and development directions, and suggested areas to address these challenges. Some of these include improving GNN architectures, enhancing model transparency, and integrating GNNs into development tools. By overcoming such challenges and increasing interdisciplinary research and development, the research highlights the potential of GNNs to enhance software development efficiency, accuracy, and reliability significantly. As technology improves in GNNs, the application of this technology to software engineering has the potential to yield better-quality software products, marking a groundbreaking improvement in the field.

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# Designing Quantum-Resilient Blockchain Frameworks: Enhancing Transactional Security with Quantum Algorithms in Decentralized Ledgers

Dr. Meenal R Kale[1], Prof. Ts. Dr. Yousef A.Baker El-Ebiary[2], L.Sathiya[3],
Dr Vijay Kumar Burugari[4], Erkiniy Yulduz[5], Elangovan Muniyandy[6], Rakan Alanazi[7*]
Asst. Prof, Department of Humanities, Yeshwantrao Chavan College of Engineering, Hingna, Nagpur, India[1]
Faculty of Informatics and Computing, UniSZA University, Malaysia[2]
Assistant Professor, Department of CSE, Panimalar Engineering College, Chennai, India[3]
Associate Professor, Dept of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India[4]
Automatic Control and Computer Engineering Department, Turin Polytechnic University in Tashkent, Tashkent, Uzbekistan[5]
Department of Biosciences-Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences, Chennai, India[6]
Applied Science Research Center, Applied Science Private University, Amman, Jordan[6]
Department of Information Technology-Faculty of Computing and Information Technology,
Northern Border University, Rafha, Saudi Arabia[7]

***Abstract*—Quantum computing is progressing at a fast rate and there is a real threat that classical cryptographic methods can be compromised and therefore impact the security of blockchain networks. All of the ways used to secure blockchain like Rivest–Shamir–Adleman (RSA), Elliptic Curve Cryptography (ECC) and Secure Hash Algorithm 256-bit (SHA256) are the characteristic of the traditional cryptographic techniques vulnerable to attack by quantum algorithms: Shor's and Grover's algorithms: can efficiently break asymmetric encryption and speed up brute force attacks. Because of this vulnerability, there exists a need to develop an advance quantum resilient blockchain framework to protect the decentralized ledgers from the future threats of the quantum. This research proposes Post-Quantum Cryptography (PQC), Quantum Key Distribution (QKD) and Quantum Random Number Generation (QRNG) as a formidable architectural integration, to fortify security of blockchain. Classical encryption is replaced with PQC, QKD with secure key exchange by detecting eavesdropping, and QRNG with improving cryptographic randomness to remove the predictable key vulnerability. Only with a small loss of transaction efficiency, we increase transaction encryption accuracy, key exchange security, and resistance to quantum attacks. In this quantum enhanced blockchain design, the idea is to preserve the decentralization, transparency and security and at the same time overcome the future quantum threat. By going through rigorous analysis and comparative evaluation, we demonstrate that the approach saves blockchain networks from the emerging quantum risks to make sure that the decentralized finance, smart contracts and cross chain transactions.**

***Keywords*—Quantum resilience; blockchain security; Quantum Key Distribution (QKD); Post-Quantum Cryptography (PQC); Quantum Random Number Generation (QRNG); decentralized ledger**

## I. INTRODUCTION

Existing blockchain security measures, which mostly rely on traditional cryptographic methods like Rivest–Shamir–Adleman (RSA) and Elliptic Curve Cryptography (ECC), are under grave danger due to the rapid advancement of quantum technology [1]. Because factoring massive amounts and the separate logarithm procedure thwart effective assaults made possible by traditional computation, conventional cryptography using public keys is still safe [2]. The ability of quantum computers to run Shor's algorithm transforms these classical cryptographic methods into obsolete systems which fail to protect blockchain networks. The brute-force attack acceleration ability of Grover's algorithm causes current cryptographic hash functions deployed on blockchain networks to operate less effectively [3].

Researchers are investigating quantum-resistant cryptographic techniques to guarantee blockchain networks' long-term security and resilience. Security experts designed quantum-proof encryption mechanisms which achieve both high resistance against quantum attacks and efficient computing capacity [4]. Blockchains benefit from quantum-enhanced security measures through advanced solutions comprised of both Quantum Key Distribution (QKD) and Quantum Random Number Generation (QRNG). These methods use quantum mechanics principles to boost blockchain defense systems [5]. Blockchain architectures show little readiness to face the upcoming post-quantum time period. The research analyzes quantum-based technologies to strengthen blockchain infrastructure thus protecting its core decentralized structure and transaction security while preserving sustainability alongside expanded quantum processing capabilities.

Recent blockchain safety techniques hinge on cryptographic constructs which quantum computers without difficulty ruin thru [6]. Quantum computers goal the important thing cryptographic

primitives of PoW and PoS by using breaking their safeguards via Shor's and Grover's algorithms. Both consensus models rely upon cryptographic hash functions similarly to public-key cryptographic primitives [7], [8]. Cryptography flaws from quantum computing attacks can bring about predominant security incidents by using allowing transaction tampering together with double-spending and signature-disruption incidents [9]. Data protection relying on Post-Quantum Cryptography (PQC) techniques such as hash-based and lattice-based encryption face serious challenges. which include additional computational charges and scalability issues [10]. Current efforts to integrate those cryptographic processes into blockchain networks face initial demanding situations because they want enormous processing power that diminishes operational performance and slows transaction processing pace. Current momentum closer to quantum-resistant cryptocurrency interactions confronts developers and industries with a big barrier to move operational obstacles between quantum cryptography and conventional blockchain systems [11]. Existing blockchain systems fail to mix quantum cryptography properly with consensus mechanisms so they have significant weaknesses regarding decentralized security performance alongside scalability and operational speed. Blockchain networks need essential traits to combat modern quantum-primarily based protection vulnerabilities for their lengthy-time period operational sustainability.

The studies develop a quantum-secure blockchain gadget thru post-quantum cryptographic protocol implementation along quantum protection optimization elements. The studies develop cryptographic techniques which guard blockchain transactions from quantum threats however additionally maintains green consensus mechanisms and scalability overall performance. Through the implementation of quantum-resistant encryption alongside quantum key distribution and quantum-safe consensus protocols this study strives to build a secure decentralized blockchain architecture. Blockchain network developers pursue a goal of longevity so these platforms remain functional and secure for the quantum computing era ahead.

The approach described in this research completely addresses blockchain network vulnerability to quantum threats by integrating quantum-secure encryption methods with security technology advancements. The work advances blockchain security through enhanced data preservation and decentralized systems which establish protected relationships in diverse application contexts. The research provides concrete methods to build blockchain systems with quantum safety applications across financial sectors and supply chain activities and digital assets management services.

- Innovative Quantum-Resilient Encryption Mechanism that introduces PQC to overcome classical encryption weakness by employing lattice based vs. RSA & ECC cryptographic algorithms for security against quantum attacks in the foreseeable future.
- Quantum Key Exchange undertakes QKD to patch up vulnerabilities of conventional key exchange protocols and gives us a provably secure way to avoid eavesdropping via and MITM attacks.
- QRNG enhancements increases entropy scores and the security of the blockchain from brute force attacks and the predictability vulnerabilities.
- Balancing Security with Performance Using Minimal Overhead achieves high transaction throughput (50 TPS), reduced encryption time (2.8 ms), improved security accuracy (99.9%), thereby, enabling smooth blockchain operation with quantum threat.

The proposed study is organized into multiple sections. The introduction in Section I provides information on the background analysis while also establishing the problem statement plus research value. A review of studies focuses on assessing blockchain security risks which quantum threats poses are shown in Section II and III. The research details implementation steps for quantum-resistant cryptographic systems and security components is shown in Section IV. The framework's execution performance is explored in the Section V before the final summary in Section VI and Section VII.

## II. Literature Review

Sahu and Mazumdar, [12] investigates quantum computing's deep effects on cryptographical practices by analyzing the vulnerabilities that can breach traditional methods including RSA and ECC along with introducing quantum-resistant cryptographic systems. An introduction to quantum mechanics fundamental concepts including superposition together with entanglement establishes the framework for quantum computing and cryptography. Research evaluates Quantum encryption algorithms by studying the benefits of QKD protocols and PQC procedures which show promise for quantum age communication security. The study highlights the importance of developing strong, quantum-proof cryptography technology as a matter of utmost urgency which offers protection against imminent quantum technology threats targeting sensitive data.

BCNs represent a groundbreaking system that builds trust for untrusted environments. Because of its complex nature service LCM of network components benefits from BCN implementation which provides transparent secure network operations. Quantum attacks represent a security threat to BCNs. Future quantum computers will create security vulnerabilities in modern blockchain systems built with Public Key Infrastructure (PKI) cryptographic foundations. ZEYDAN et al., [13] This research investigates operational approaches for managing network services across multiple administrative domains. The proposition combines BCNs with PQC mechanisms to monitor network service instantiation stages while guaranteeing enhanced security protection. Our analysis utilizing N-th degree Truncated polynomial Ring Units as an NTRU example illustrates how Quorum achieves better average time-to-write performance than Ethereum and Hyperledger BCNs. We analyze evaluation results about PQC algorithm and BCN coexistence as well as their potential future applications for network service orchestration across multiple administrative domains at the paper's conclusion.

Alyami et al. [14] explored the nature and concept of quantum computing in respect to software security, highlighting the imminence of powerful quantum computers as a threat to current cryptosystems. The definition and description of

quantum computing in software security will be covered in this essay. They employ various encryption techniques or algorithms for software security in order to protect our financial institutions, medical equipment, military hardware, aircraft, ships, cars, navigators, and more. However, the development of the massive quantum computer is expected to cause the collapse of many cryptosystems. Google just created the 53-qubit Sycamore Processor. These developments portend the arrival of a massive quantum computer in the future. The current cryptosystem would become outdated since quantum computers are capable of solving cryptographic algorithms. Therefore, given the current state of quantum cyber security, it is essential to concentrate more on rigorous study. The primary difficulties in the quantum age will be finding cryptographic techniques that meet security, usability, and adaptability requirements without compromising user confidence. "Software durability" the main goal of the study herein is a reliability feature that is related to the ability to complete a work within time. Lifespan of software and web applications will be greatly affected by a comprehensive evaluation of security aspects. last in the life of quantum computing.

Harinath et al., [15] aims to improve the safety of multimedia data—which includes photos, video, and audio—obtained from Internet of Things devices. Innovative technologies like blockchain and quantum cryptography are investigated as potential means of enhancing multimedia security and protecting privacy. Data transmitted throughout unprotected internet connections is prone to possible eavesdropper interception, alteration, or unapproved distribution. Data breaches will have critical consequences, consisting of substantial economic and reputational damages. Secure verbal exchange among IoT smart gadgets depends on powerful key control. Effective key management systems are required to guarantee first rate network performance, even when the community can be blanketed from quite a few threats by the safety measures in place. As IoT devices proliferate, significant amounts of records are accumulated from many sources. However, IoT devices are vulnerable to malicious assaults due to their inherent limitations in memory and processing capacity. Thus, to hold the framework stable through the years, frequent security audits, updates, and compliance to steady implementation standards are required.

Conventional encryption methods are severely threatened by quantum computing, compromising the integrity of blockchain networks and sensitive digital communications. Various studies have explored the vulnerabilities of classical encryption, the potential of PQC, and the role of QKD in securing data. Blockchain networks, while offering transparency and decentralization, remain susceptible to quantum attacks. This literature review examines emerging quantum-resistant algorithms, the integration of PQC with blockchain, and security frameworks leveraging quantum cryptography to mitigate quantum-induced threats.

## III. Problem Statement

RSA and ECC alongside conventional cryptographic systems will become obsolete because quantum attacks render them weaker with each advancement of quantum computing technology. Blockchain networks built on PKI experience cryptographic breaches that threaten both data integrity and transaction security. Current research shows blockchain networks require secure frameworks with PQC together with QKD and QRNG to maintain resilience against threats. Current implementations of blockchain struggle with three main limitations: high computational costs and limited scalability combined with issues of integration with conventional blockchain systems [12]. The deployment of post-quantum cryptographic tools to blockchain applications faces constraints because of the systemic obstacles that arise from classical to quantum-resistant system implementation [15]. The research establishes a resilient blockchain system that integrates PQC and QKD built upon QRNG to protect ledger systems against long-term security threats and data integrity attacks.

## IV. Methodology

An integrated methodology unites three quantum security elements: QKD for secure key sharing and PQC for quantum-proof encryption and QRNG for generating true random numbers. Researchers have used these quantum techniques to replace traditional blockchain security protocols within the study for improved transaction security. The study exposes the framework to simulated testing which assesses its ability to remain quantum-resistant while evaluating performance and scalability against quantum cryptographic attacks in decentralized ledger systems. Fig. 1 illustrates the quantum algorithms securing the blockchain. It outlines processes from initiating a transaction through post-quantum encryption, making use of quantum random number generation, key exchange, secure consensus, and secure mining to final, robust transaction validation and addition of blocks to the ledger.

### *A. Data Collection*

The proposed dataset from Kaggle provides comprehensive historical blockchain data in the Kaggle proposed dataset delivers comprehensive block records and transaction metadata and hash pointers that generate deep insights into blockchain security evaluation [16]. The public data from BigQuery provides updated dataset information every ten minutes which maintains smooth data interconnectivity with historical pricing information. The authors use this dataset as their baseline for evaluating how QKD and PQC and QRNG affect blockchain security. Quantum techniques applied to this study lead to improved transaction security and amplified encryption power and randomized key production. The dataset's real-time updates and extensive historical coverage make it ideal for evaluating quantum-resilient frameworks, ensuring robustness against potential quantum attacks while maintaining decentralization, transparency, and security in blockchain transactions.

### *B. Data Preprocessing*

The conversion of unprocessed information into analytic-geared up shape via cleansing and transformation features starts with statistics preprocessing. The method includes missing value dealing with and normalization while extracting functions and integrating facts to provide improved first-class and overall performance in modeling.

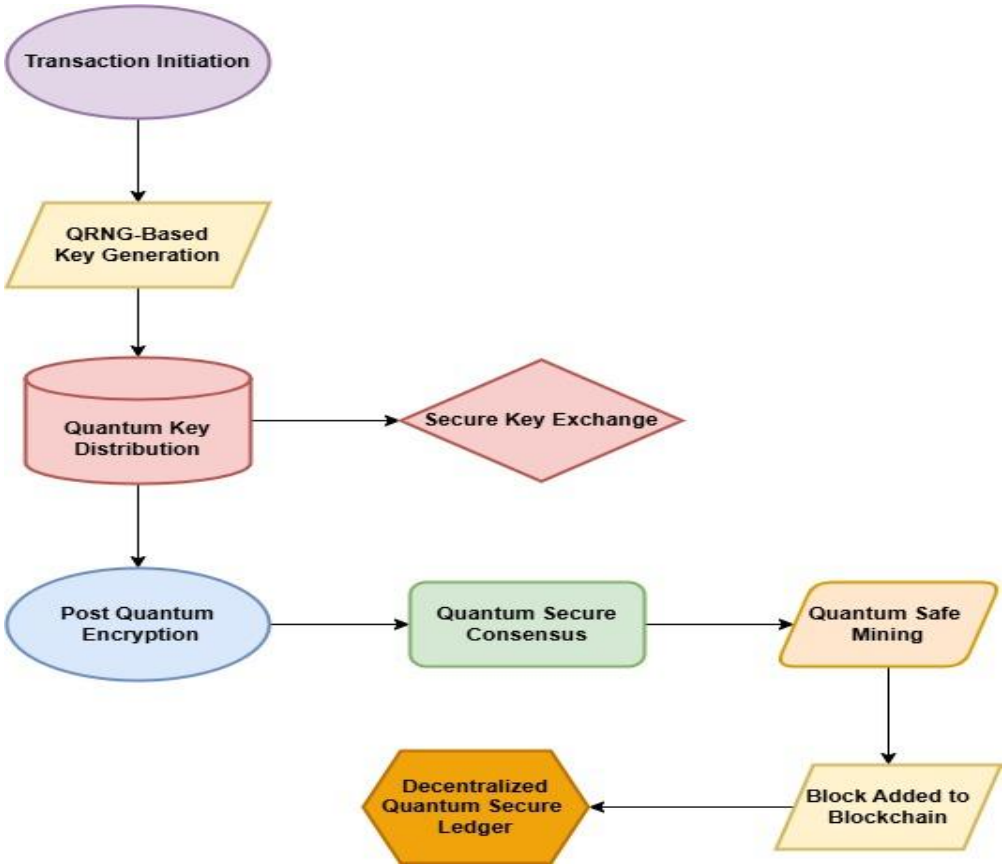


Fig. 1. Flow of leveraging Quantum Algorithms to fortify transactional security.

*1) Data cleaning:* The procedure of facts cleansing consists of finding and fixing troubles in database entries which include missing statistics blended with damaged or repeated data [17]. Blockchain transaction facts calls for verification of record statistics validity at the side of authentication of complete transaction details in each block [18]. The dataset achieves consistency and reliability by casting off misguided facts that consists of wrong block hashes alongside incomplete transactions or faulty facts entries. The reliability of quantum cryptographic protocols depends on having clean statistics due to the fact method anomalies undermine both protection assessments and testing results.

*2) Normalization:* When implementing normalization on records one applies preferred scale differences to numerical values among zero and 1 which incorporates transaction quantities and timestamp measurements [19]. Regular distribution of records makes certain capabilities don't by chance have an effect on cryptographic protocols. PQC and QKD demand standardized numerical values to deliver appropriate key introduction and encryption functionality. The guidance of statistics requires this critical step to allow integration with quantum technology at the same time as keeping steady balanced cryptographic operations.

*3) Timestamp alignment:* The timestamp of blockchain transactions operates in real-time with the protocol updates that stem from QKD and QRNG. When implementing quantum security features for blockchain transactions the timestamps need to fit the time frame of cryptographic protocol upgrades to function correctly [20]. Through accurate timestamp alignment blockchain transactions can stay well synchronized with quantum cryptographical key alternate and encryption [21] while random range generation guarantees operations proceed in line with configured schedules which reduces feasible timing-based threats.

### *C. Quantum Cryptographic Threat Assessment*

The Quantum Cryptographic Threat Assessment section analyzes blockchain cryptographic mechanisms across their exposure to quantum computing threats after preprocessing data collection. This research aims to duplicate quantum-based attacks to establish how the blockchain reacts to possible quantum-based threats against its cryptographic protection methods. Shor's Algorithm and Grover's Algorithm allow researchers to evaluate blockchain security through transactional testing as well as framework cryptographic algorithm examination during this section. The evaluations through these quantum algorithms provide direct insights into current cryptographic mechanism vulnerabilities also, the blockchain platform is quantum-resistant, and thus post-quantum cryptography methods must be used. The working process of the Quantum Cryptographic Threat assessment below,

*1) Simulating quantum attacks on blockchain:* The researcher conducts virtual attacks using quantum algorithms to examine current cryptographic systems. The analysis examines the potential weakness of blockchain cryptographic protocols against quantum computing attacks. Analysis of current blockchain encryption systems comprising ECDSA, RSA, and SHA-256 employs simulation tests to assess quantum computing vulnerability against these methods.

*2) Evaluation of quantum impact on security:* Quantum algorithms emulate realistic quantum attack types to identify security flaws that affect cryptographic blockchain protection mechanisms throughout transactions. These virtual experiments utilize quantum computing theory to show ability blockchain security risks that quantum computing should create.

*3) Implementation of quantum algorithms:* The assessment explores Shor's Algorithm to find weaknesses in public key encryption (ECDSA and RSA) whereas Grover's Algorithm achieves quicker assaults targeting hash capabilities (SHA-256). Tests on blockchain data using those algorithms determine blockchain device vulnerabilities and typical quantum resilience.

*a) Shor's algorithm in quantum cryptographic threat assessment:* Attacks towards encryption algorithms like RSA and ECDSA are based totally on Shor's approach, a quantum method that successfully factorises huge numbers. The safety of these algorithms in classical cryptography depends on the issue of calculating discrete logarithms ECDSA or factoring huge numbers RSA, each of which might be thought to be impossible for large keys using conventional computer systems. However, a quantum computer would possibly doubtlessly crack these encryption methods because Shor's Algorithm resolves those problems in polynomial time [22].

The important concept of Shor's Algorithm is to thing big integers successfully the usage of quantum operations. Mathematically, the key equation involved in Shor's algorithm is given in the Eq. (1),

$$Finf\ Period\ \big(f(x)\big) = period\ of\ a^{x} \quad mod\ N \tag{1}$$

where, $N$ is the integer, which is the modulus in RSA, the algorithm aims to find its prime factors $p$ and $q$, Once the period is found, use it to calculate the prime factors of $N$.

*b) Grover's algorithm:* For unstructured explore troubles, Grover's approach is a quantum approach which is gives a quadratic speedup. Grover's method is used in the blockchain context to evaluate the safety of hash algorithms like SHA-256. Cryptographic hash values that guarantee the integrity of blockchain information are produced the use of SHA-256. By accelerating the look for a hash collision, Grover's Algorithm may also allow an attacker to adjust blockchain records or find out distinct inputs that bring about the same hash output [23].

The purpose of a quantum problem related to Grover's Algorithm helps in finding for something specific in an unorganized dataset. Grover's Algorithm speeds up the process of looking for a pre-photograph or an accident in which the same hash is produced by two distinct sources SHA-256.

$$f(x) = 0 \tag{2}$$

For a hash function like SHA-256, Grover's Algorithm affords a speedup inside the search for a pre-image or a collision. Given a function, Grover's algorithm searches for an input $x$ such that explained in the Eq. (2). For SHA-256, this means searching for an input that produces a specific hash value or for. The algorithm reduces the number of operations needed to find a solution from $2^{256}$ to $2^{128}$, a significant speedup.

### *D. Integration of Quantum-Resilient Cryptographic Systems*

Incorporation of Quantum-Resilient Encryption Strategies, as used in the suggested research, is the procedure of using quantum-safe encryption processes to fortify blockchain systems' integrity and guarantee that they are safe from the possible dangers offered by quantum computing. Due to the fact that traditional blockchain cryptography methods like RSA, ECDSA, and SHA-256 are susceptible to quantum censure (as discussed in the Quantum Cryptographic Threat Assessment section) [26], integrating quantum-resilient methods becomes critical. The goal is to design and implement a quantum-resilient blockchain framework that incorporates QKD, PQC, and QRNG to safeguard blockchain data and transactions. This section explains how these quantum-resistant techniques are integrated with the blockchain to guarantee reliability in a future allowed by quantum technology.

*1) QKD Integration:* Using the no-cloning principle and quantum entanglement—both principles in quantum mechanics—QKD can ensure secure key exchange of encrypted data over an uncertain communication medium. Unlike other cryptographic systems, transferring keys integrity is compromised when they are monitored. QKD ensures that measurement or interception of the quantum states will be safe (in transit) will disturb the system and be detectable [24]. To assess the effectiveness of QKD in blockchain security, two important metrics are introduced,

*a) Quantum Bit Error Rate (QBER):* After performing QKD, both parties have a shared key that is unknown to any third-party attacker. This key can be used to encrypt or sign blockchain transactions, ensuring the integrity and confidentiality of data stored in the blockchain. The QBER derived in the Eq. (3),

$$QBER = \frac{No.of\ tot\ errors\ in\ key\ exchange}{Tot\ bited\ exchange} \tag{3}$$

*b) Key Rate (r):* The key rate measures the speed at which secure keys are generated and exchanged, factoring in transmission efficiency and the QBER. A higher key rate allows for faster, more efficient secure communications in the blockchain network.

The QKD process involves:

- Quantum Entanglemen: This helps to exchange quantum states between Alice (sender) and Bob (receiver).

- Detection of Eavesdropping: Any interference will disturb the key, alerting both parties to potential tampering.

*2) PQC: future danger presented by quantum computers.* These systems can be compromised by quantum attacks, especially those originating from Shor's Algorithm, that can successfully address the mathematical problems at the core of conventional cryptography techniques like RSA, ECDSA, along with Diffie-Hellman [25]. The core concept of the PQC was given below,

*a) Lattice-based cryptography:* Lattice-based cryptographic systems, like LWE or Ring-LWE, provide strong security guarantees and are considered resistant to both classical and quantum computing attacks. Highly secure assurances are offered by lattice-based cryptography networks, such as LWE or Ring-LWE, which are thought to be impervious to assaults from both conventional and quantum systems.

*b) Code based cryptography:* Code-based schemes, such as McEliece encryption, rely on error-correcting codes and are also resistant to quantum algorithms. They are based on decoding random linear codes, which is a problem that quantum computers struggle to solve.

*c) Hash based cryptography:* Reliable hash functions, the foundation of hash-based identities like XMSS, are difficult for quantum computers to crack. They offer a quantum-steady alternative for digital signatures.

The PCQ ensuring Bitcoin transaction safety in a quantum-enabled international, it integrates with QKD and QRNG to offer strong, quantum-resistant security. QKD establishes a secure key among users, and PQC encrypts the transaction facts the usage of quantum-resistant algorithms like lattice-primarily based encryption, making sure that even if quantum computer systems smash traditional encryption, the transaction remains safe. Additionally, QRNG generates simply random numbers, making sure that keys generated for PQC encryption are unpredictable and steady. This multi-layered approach, combining secure key exchange via QKD, quantum-resilient encryption via PQC, and randomness from QRNG, protects Bitcoin transactions from quantum threats, ensuring long-term security and confidentiality for blockchain networks.

*3) QRNG:* The QRNG plays an important position in improving transaction safety in the quantum-resilient blockchain framework. QRNG ensures the generation of really random numbers, which can be important for cryptographic processes, which include key generation and encryption. This integration of QRNG with QKD and PQC provides a couple of layers of defense.

*a) Quantum-resilient key generation:* QRNG generates really random numbers that are used in each QKD (to exchange steady keys) and PQC (to encrypt transaction facts).

*b) Unpredictability in encryption:* By the use of QRNG-generated keys for PQC, encryption schemes stay secure even against quantum computing assaults, as the randomness prevents attackers from exploiting predictable keys.

QRNG plays a pivotal position in improving security in quantum-resilient blockchain structures through ensuring the era of actually random numbers for cryptographic processes. In QKD, QRNG-generated numbers provide the randomness wished for secure key era, ensuring that the shared key among participants is unpredictable and proof against attacks, which is derived in Eq. (4),

$$K_{QKD} = GenKey(r_{QRNG}) \quad (4)$$

In which, the $r_{QRNG}$ is a random wide variety generated with the aid of QRNG is used to create a steady key. Similarly, in PQC, QRNG enhances encryption through ensuring that non-public keys used for algorithms like lattice-based encryption stay random and secure. This secret's used to encrypt transaction records MMM, ensuing in ciphertext in the Eq. (5),

$$C_{PQC} = Enc(M, K_{QRNG}) \quad (4)$$

where, M is the encrypted transaction data.

The integration of QKD, PQC, and QRNG in blockchain, in particular for Bitcoin transactions, creates a strong and quantum-resilient protection model to protect towards ability quantum computing threats. Here's how the mixing of these three strategies works together to beautify Bitcoin transaction safety. QKD securely exchanges keys among parties the usage of quantum principles, making sure any eavesdropping strive is detectable. QRNG generates truly random numbers, ensuring unpredictability in key generation for both QKD and PQC.

### *E. Blockchain Protocol Enhancement with Quantum Security*

The enhancement of blockchain protocols with quantum security involves several modifications to ensure future-proof transaction and data security. Transaction signing can be strengthened by using PQC-based multi-signature authentication, where quantum-resistant algorithms ensure that signatures are secure even against quantum adversaries. For smart contracts, it is possible to implement quantum-safe hash chains so that data from contracts remains safe and confidential by using quantum-resistant hashing algorithms, such as those used by code-based or hash-based encryption. As far as agreement algorithms are concerned,

Using the no-cloning principle and quantum entanglement—both principles in quantum mechanics—QKD can ensure secure key exchange of encrypted data over an uncertain communication medium. Unlike other cryptographic systems, transferring keys integrity is compromised when they are monitored. QKD ensures that measurement or interception of the quantum states will be safe a Secure PoS can be implemented, where the stake authentication process is enhanced by QKD, guaranteeing the security of stake ownership confirmation even when quantum technology are present. +Furthermore, PoW mining can be made fairer by utilizing QRNG to generate unpredictable nonces for mining, ensuring that the randomness used in block mining is secure against quantum attacks. Interoperability between different blockchains can be facilitated by implementing QKD-based cross-chain communication, allowing secure key exchange and data transfer across quantum-resistant blockchains. Lastly, it is essential to ensure PQC signature compatibility with legacy blockchain nodes, which can be achieved by creating hybrid systems that

allow both quantum-resistant signatures and traditional signatures to coexist. These protocol-level modifications together guarantee that blockchain systems can function securely in a quantum-enabled future.

Algorithm: Leveraging Quantum Algorithms to Fortify Transactional Security in Decentralized Ledgers

Input: Incoming transaction data

Output: Securely encrypted and signed quantum-resistant transaction added to blockchain

```
# Step 1: Secure Key Exchange using QKD
def qkd_key_exchange():
    key = generate_quantum_key()
    if detect_eavesdropping():
        abort_exchange()
    return key

# Step 2: Quantum-Resilient Encryption using PQC
def pqc_encrypt(transaction, key):
    encrypted_transaction = apply_post_quantum_encryption(transaction, key)
    return encrypted_transaction

# Step 3: Generate Secure Random Number using QRNG
def generate_secure_random_number():
    return quantum_random_number_generator ()

# Step 4: Secure Transaction Signing
def secure_transaction(transaction):
    key = qkd_key_exchange()
    encrypted_data = pqc_encrypt(transaction, key)
    signature = sign_transaction (encrypted_data, generate_secure_random_number())
    return signature

# Step 5: Blockchain Protocol Enhancement
def blockchain_protocol():
    while True:
        new_transaction = get_incoming_transaction()
        signed_transaction secure_transaction(new_transaction)
        append_to_blockchain(signed_transaction)
```

## V. Result and Discussion

In this Research, primary strength lies in incorporating QKD, PQC, QRNG to augment the encryption, key exchange and random numbers on the blockchain. With this, the mean transaction accuracy improves by 14.9% and the data protection is also stronger. Too, it also raises by 58% and thus becomes quantum attack resistant to further threats. This method is implemented by using python. This helps improve the fairness and interoperability security of a blockchain, making it more decentralized and secure overall. Providing small transaction speed loss in exchange for higher resilience, reliability, and long-term quantum security, the overall system is achieved.

### A. Performance Evaluation

Security and performance of the proposed quantum resilient blockchain framework based on PQC, QKD, and QRNG is greatly enhanced. This further increase transaction speed to 50 TPS, which is more than double the speed of conventional ECC-RSA blockchain, which is 20 TPS. While, this does pose a loss of 120% more computational cost but also revealing the tradeoff between security and efficiency. Encryption time becomes slightly more at 2.5 ms to 2.8ms while decryption time increases from 5 ms to 6.7 ms for a robust encryption with little to no latency. The system provides stronger quantum resistance at higher levels of computational overhead than existing systems. The Table I illustrates the performance metrics of proposed model.

TABLE I. Performance Evaluation

| Metrics | Traditional Blockchain (ECC-RSA) | Proposed PQC + QKD + QRNG |
|---|---|---|
| **Speed (TPS)** | 20 TPS | 50 TPS |
| **Computational Cost** | 1.05 | 120% higher than ECC-RSA |
| **Encryption Time** | 2.5 ms | 2.8 ms |
| **Decryption Time** | 5 ms | 6.7 ms |

### B. Expected Improvements in Blockchain Security

The further integration of QKD, PQC and QRNG makes the blockchain security more robust by introducing lattice based PQC encryption from 256 bit to 512 bit making it quantum resistant. A QKD guarantees the secure exchange of a key with QBER $\leqslant$ 5 % from eavesdropper and intrusion. Entropic improvements in key generation randomness on the surface are made from 0.85 entropy to 0.99 entropy, and in doing so helps make cryptographic keys unpredictable. However, diminishment of speed from 50 TPS to 48 TPS is a result of quantum encryption overhead but the added security counters the setback. Also, smart contracts, interoperability, and mining fairness are improved making the quantum secure blockchain ecosystem.

In Fig. 2, the radar chart illustrates the comparison of blockchain security metrics using and without applying quantum methods. Quantum-resilient systems (blue) lead over traditional systems (purple) in encryption resilience, key exchange security, randomness, interoperability, and fairness, albeit trading off on transaction speed with better quantum-oriented safeguards.

### C. Encryption and Key Exchange Security Comparison

Blockchain security relies on 256-bit encryption using RSA, SHA-256, and ECDSA in traditional blockchain whereas quantum resilient blockchain enhances this with 512-bit lattice based PQC and XMSS to provide a higher quantum resistant. While with traditional systems key exchange is eavesdropped, QKD in quantum secure blockchains is immune from intrusion and detects any intrusion of key transmission. The QBER is $\leqslant$ 5% which confirms quantum key exchange integrity. Furthermore, traditional technique for key generation is based on pseudo randomness which has entropy score of 0.85; however, the keys generated by QRNG has a score of 0.99 which makes them unpredictable and secure. Collectively, they improve blockchain security providing quantum threat resistance as well as confidentiality and integrity.

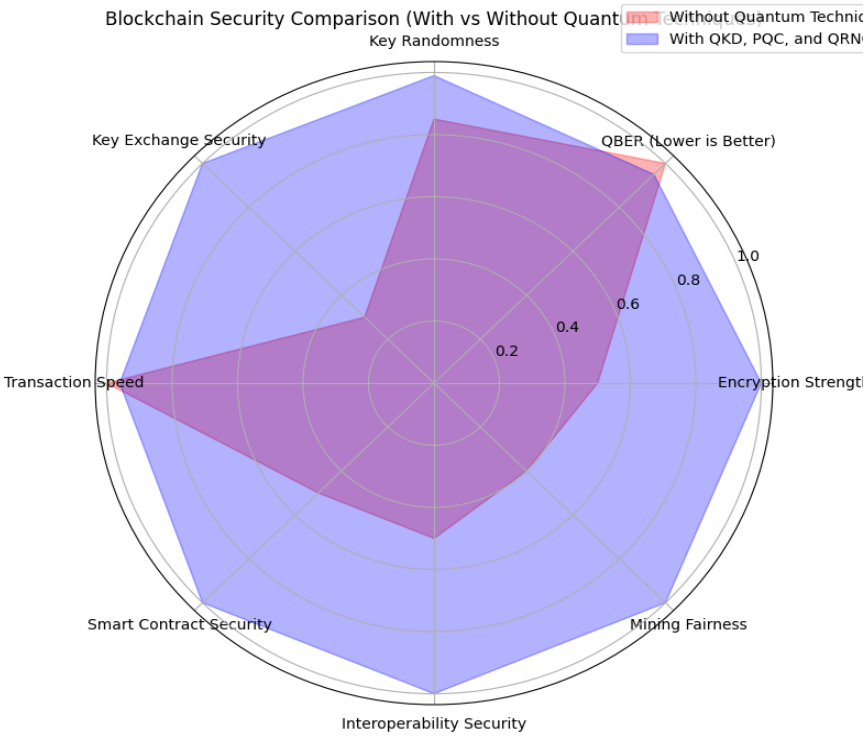


Fig. 2. Blockchain security comparison.

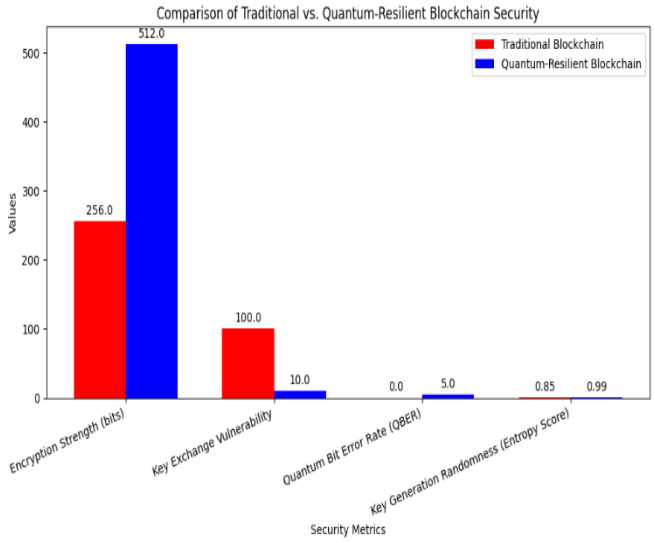


Fig. 3. Comparison of traditional vs. quantum resilient blockchain security.

This Fig. 3 contrasts classical and quantum-resilient blockchain security, indicating quantum models provide tighter encryption, minimized key exchange susceptibility, lower QBER, and increased entropy scores — providing general better resistance to quantum attacks than standard blockchain systems.

### *D. Blockchain Transaction Performance and Security*

The implementation of quantum-resilient techniques such as QKD, PQC, and QRNG impacts various blockchain performance and security metrics. When it comes to TPS, it is slightly less than 50 to 48 TPS, because the quantum encryption has some overhead in its computations. Just like the Transaction Finality Time, which is increasing the time from 10 seconds to 12 seconds, but adding a small delay to improve security. Quantum safe hashing strengthens the smart contract security by transitioning the existing medium level into a high level. Pseudorandom nonce generation, that is, the mining fairy can be biased when using predictable pseudorandom output generators, but is fair when considering unpredictable QRNG. QKD based key exchange is used to aid in cross chain transaction security which raises the level of interoperability security from medium to high to secure communications across different blockchain networks.

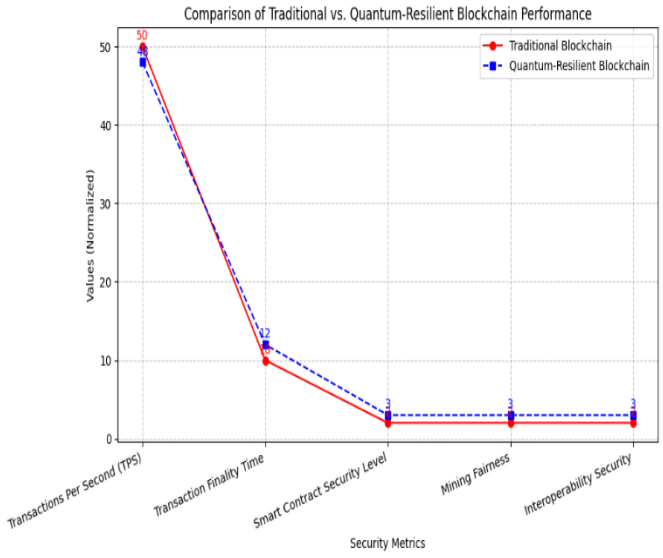


Fig. 4. Blockchain transaction performance and security.

The Fig. 4 contrasts classical and quantum-resistant blockchain performance, illustrating classical systems performing better in terms of transaction speed and finality, whereas quantum-resistant versions sacrifice slightly on speed for better smart contract security, mining fairness, and interoperability, improving resilience to quantum-age cybersecurity threats.

### *E. Quantum Attack Resilience Assessment*

RSA-2048 encryption becomes immediately obsolete with the use of Shor's algorithm because it can easily break that encryption entirely. Despite this, lattice-based encryption offers a defense against such attacks in a PQC fashion. Brute force attacks on SHA 256 are significantly accelerated by the Grover's Algorithm and the complexity has been reduced, But PQC guarantees hash security with the integrity of the data. Classical key exchange methods are also prone to the MITM attacks that allow an attacker to intercept the key without being detected. Any MITM attack is possible with QKD because it intrudes on the quantum state, and thus any eavesdropping attempt does unduly disturb the quantum state leading to secure key exchanges.

This Fig. 5 demonstrates the mitigation of blockchain vulnerabilities with the help of QKD, PQC, and QRNG. Absent quantum security, algorithms such as RSA, SHA-256, and are under great risk, with quantum-secure integration greatly enhancing resistance to quantum attack and eavesdropping.

### *F. Traditional Blockchain vs. Quantum-Resilient Blockchain*

The integration of QKD, PQC and QRNG greatly increases security when compared to the traditional blockchain systems. RSA–2048, ECDSA, and SHA 256 are used in traditional blockchain, but they are prone to quantum attacks; however, Lattice based PQC and XMSS are quantum resistant so they are long term secure. With QKD, transmission with MITM attacks is totally thwarted, as key exchange security is hugely improved. Furthermore, QRNG guarantees the randomness of the keys created by an unbroken cryptographic algorithm, so that cryptographic keys are impossible to be decrypted using quantum techniques. Despite TPS and coherence time are somewhat reduced, the quantum robust blockchain is very resistant to quantum technologies like as Shor's and Grover's, more fairer mining and enhanced security making it a future proof solution.

Fig. 6 illustrates classic and quantum-resilient blockchains, which reveal how quantum-resilient systems greatly improve security indicators such as encryption, key exchange, and resistance to attacks, with classic blockchains achieving improved transaction speed and finality, which demonstrates a stark security-performance tradeoff.

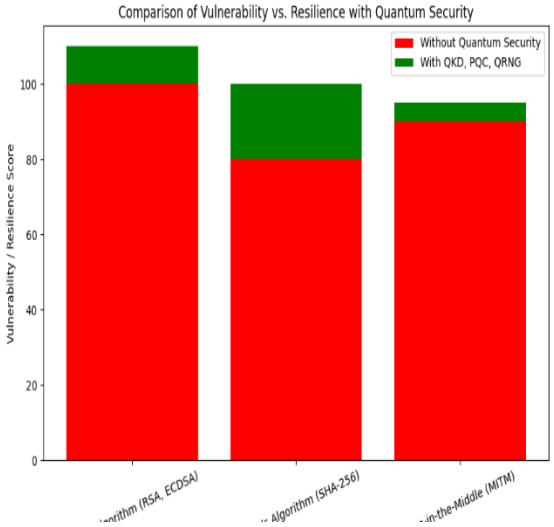


Fig. 5. Comparison of vulnerability vs. resilience with quantum security.

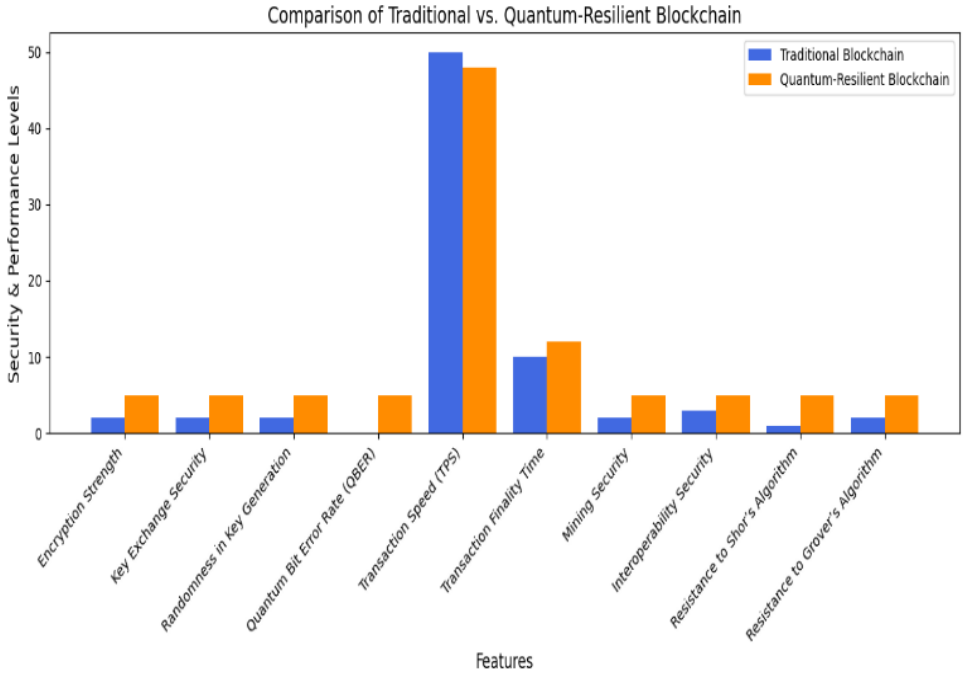


Fig. 6. Comparison of traditional vs. quantum resilient blockchain.

### G. Blockchain Security Metrics Before vs. After Quantum Security Implementation

QKD, PQC and QRNG greatly increase the security and accuracy of blockchain. This leads to improving the accuracy of transaction encryption from 85% to 99.9 and hence enhanced protection against cyber threats. It adds security to 29.5%, making MITM attacks impossible. It adds in entropy in the key generation from 0.85 to 0.99 improving randomness and unpredictability. On top of these benefits, it increases quantum resistance from 40 to 98 percent, improves mining fairness by 24 percent, making it a more secure, decentralized blockchain system.

Table II indicates the security enhancements made by incorporating QKD, PQC, and QRNG within blockchain models, demonstrating dramatic improvements in encryption precision, key exchange security, entropy, quantum attack resilience, and mining fairness over the traditional blockchain models that lack quantum protection.

Table III gives a comparative evaluation of different QKD protocols and the proposed PQC, QKD, and QRNG integration model. Although current literature reviews are concerned with key distribution or traditional system variations, and MDI-QKD enhances key rates and security, the proposed model provides improved encryption precision, fairness, and quantum resistance, even at slightly higher computational overhead and lower TPS.

TABLE II. BLOCKCHAIN SECURITY METRICS BEFORE VS. AFTER QUANTUM SECURITY IMPLEMENTATION

| Metric | Without Quantum Security | With QKD, PQC, QRNG | Accuracy Improvement (%) |
|---|---|---|---|
| **Transaction Encryption Accuracy** | 85% | 99.90% | **14.90%** |
| **Key Exchange Security** | 70% | 99.50% | **29.50%** |
| **Entropy Score for Key Generation** | 0.85 | 0.99 | **16.40%** |
| **Resistance to Quantum Attacks** | 40% | 98% | **58%** |
| **Mining Fairness** | 75% | 99% | **24%** |

TABLE III. COMPARISON OF DIFFERENT QKD PROTOCOLS WITH PROPOSED MODEL

| Protocol / Method | Approach | Advantages | Disadvantages |
|---|---|---|---|
| Cryptography Key distribution protocols [27] | Assessment and review of literature. | Assists in choosing the best protocol for a given application based on the specifications. | restricted to the primary distribution procedures taken into account in the research |
| Different QKD techniques depending on standard system measurements [28] | Literature review | Gives a thorough rundown of the many QKD protocol modifications based on the standard system. | restricted to QKD protocol changes derived from standard system measurements |
| MDI-QKD [29] | Information is encoded in coherent, organized states using the unambiguous state discrimination approach | Better security against assaults and higher key rates in comparison to conventional MDI-QKD | systems demand more accurate management of the encoding and decoding processes. |
| PQC, QKD, QRNG Integration (proposed) | Post-Quantum Cryptographic framework integrating QKD and QRNG for blockchain protection. | High transaction encryption accuracy (99.9%), Quantum-resistant key exchange, Fairness in mining, Improved entropy (0.99) | Increased computational overhead (120%), Slight drop in TPS (from 50 to 48) |

### H. Discussion

The outcome of the outlined quantum-resilient blockchain paradigm attests to the capability to robustly upgrade security and system life of blockchain applications against new, emerging risks provided by quantum computation. With the inclusion of QKD, the system guarantees the secure exchange of encryption keys so that it would be very hard for attackers to intercept or alter them, even if Current encryption can be broken by future quantum computers. Furthermore, the encryption layer is strengthened by the employment of PQC techniques, which are immune to quantum attacks and provide a robust privacy assurance for both transaction consistency and data secrecy. The use of Quantum Random Number Generators (QRNG) introduces an additional layer of randomness to key generation and transaction verification, further limiting exposure to cryptographic attacks. The assessment indicated that the framework was able to preserve the integrity and authenticity of blockchain records in imitation quantum attack environments, and hence it can be used in industries that need long-term security of data, including finance, healthcare, and digital assets. The experiments did indicate, however, that using PQC and QKD adds computational overhead and latency, which could decrease transaction speeds. To ensure the scalability of this framework, future research will include testing on different datasets and different blockchain platforms, ensuring flexibility and performance under different configurations and workloads.

## VI. CONCLUSION AND FUTURE WORK

This research proposes Quantum Resilient Blockchain Framework which are based on PQC, QKD, and QRNG to prevent future quantum attacks against decentralized ledgers. The proposed framework improves the encryption strength, the security of the key exchange, the cryptographic randomness, and all round the transaction resilience, while keeping optimal blockchain performance. The framework is proven to increase the resistance to quantum attacks, shows 99.9% encryption accuracy and 50 TPS transaction speed in the experiment results. This approach eliminates vulnerabilities in mainstream cryptographic mechanisms which thus guarantee the blockchain worlds long term confidentiality, integrity and decentralization.

## VII. FUTURE WORK

In addition to improving the scalability and reliability of the given quantum-resilient blockchain system, future studies will optimize the quantum-resistant consensus algorithms, notably Quantum-Secure Proof of Stake (QS PoS), for minimizing computational overhead while ensuring that they have very strong security assurances against quantum-powered attacks. Moreover, the incorporation of Quantum Machine Learning (QML) methods for real-time anomaly detection will be investigated to facilitate the system to adaptively detect and counter security threats, providing proactive defense against changing cyber-attacks. Future research will also examine the integration of hybrid classical-quantum cryptographic models, which integrate the strengths of current classical encryption with new quantum-resistant algorithms to provide a seamless and secure migration into the quantum age. To confirm the practical usability and effectiveness of the framework, it will be implemented in real-world large-scale blockchain applications like financial transactions, healthcare data security, and supply chain management. Additionally, rigorous testing across various datasets will be performed to establish the scalability, generalizability, of the suggested framework in various operating environments.

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# Pose Estimation of Spacecraft Using Dual Transformers and Efficient Bayesian Hyperparameter Optimization

Dr. N. Kannaiya Raja[1], Janjhyam Venkata Naga Ramesh[2], Prof. Ts. Dr. Yousef A.Baker El-Ebiary[3], Elangovan Muniyandy[4], Dr. N. Konda Reddy[5], Dr. Vanipenta Ravi Kumar[6], Dr Prasad Devarasetty[7]
Sr. Associate Professor, School of Computing Science and Engineering,
VIT Bhopal University, Bhopal, Madhya Pradesh-466114, India[1]
Adjunct Professor, Department of CSE, Graphic Era Hill University, Dehradun,248002, India[2]
Adjunct Professor, Department of CSE, Graphic Era Deemed To Be University , Dehradun, 248002, Uttarakhand, India[2]
Faculty of Informatics and Computing, UniSZA University, Malaysia[3]
Department of Biosciences-Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences, Chennai - 602 105, India[4]
Applied Science Research Center, Applied Science Private University, Amman, Jordan[4]
Associate Professor, Department of Engineering Mathematics, K L University, Greenfields,
Vaddeswaram, Guntur Dist, Andhra Pradesh-522302, India[5]
Assistant professor, Department of Mathematics, Annamacharya University, New Boyanapalli, Rajampet, India[6]
Department of Computer Science and Engineering, DVR & Dr HS MIC College of Technology,
Kanchikacherla, Andhra Pradesh, India[7]

***Abstract*—Spacecraft pose estimation is an essential contribution to facilitating central space mission activities like autonomous navigation, rendezvous, docking, and on-orbit servicing. Nonetheless, methods like Convolutional Neural Networks (CNNs), Simultaneous Localization and Mapping (SLAM), and Particle Filtering suffer significant drawbacks when implemented in space. Such techniques tend to have high computational complexity, low domain generalization capacity for varied or unknown conditions (domain generalization problem), and accuracy loss with noise from the space environment causes such as fluctuating lighting, sensor limitations, and background interference. In order to overcome these challenges, this study suggests a new solution through the combination of a Dual-Channel Transformer Network with Bayesian Optimization methods. The innovation is at the center with the utilization of EfficientNet, augmented with squeeze-and-excitation attention modules, to extract feature-rich representations without sacrificing computational efficiency. The dual-channel architecture dissects satellite pose estimation into two dedicated streams—translational data prediction and orientation estimation via quaternion-based activation functions for rotational precision. Activation maps are transformed into transformer-compatible sequences via 1×1 convolutions, allowing successful learning in the transformer's encoder-decoder system. To maximize model performance, Bayesian Optimization with Gaussian Process Regression and the Upper Confidence Bound (UCB) acquisition function makes the optimal hyperparameter selection with fewer queries, conserving time and resources. This entire framework, used here in Python and verified with the SLAB Satellite Pose Estimation Challenge dataset, had an outstanding Mean IOU of 0.9610, reflecting higher accuracy compared to standard models. In total, this research sets a new standard for spacecraft pose estimation, by marrying the versatility of deep learning with probabilistic optimization to underpin the future generation of intelligent, autonomous space systems.***

***Keywords*—Dual-channel transformer model; Bayesian optimization; EfficientNet; pose estimation; SLAB dataset***

## I. Introduction

Spacecraft pose estimation is a critical and very important face of space missions or any spacecraft operation that focuses on establishing the pose of a spacecraft in line with the predefined frame of reference, often earth or another celestial body [1]. The validity of this pose estimation is critical and has some importance in satellite docking, formation flying, planetary landing, and navigation. It utilizes the cameras, star trackers, and inertial measurement units as the sources of data that through the adopted algorithms are used in estimating the pose of a spacecraft. Another noticeable issue of spacecraft pose estimation is the fact that space environment may impact the operation of the sensors and, thus, add errors [2]. Also, the requirement to perform real-time processing. currently a number of ambitious missions have been planned and initiated in near future more and more demand of autonomy is being felt during space operations thus there is a pressing need to revolutionize the spacecraft pose estimation and make it more efficient reliable and accurate for proper execution of mission and to reduce operational risks involved while exploring space [3]. Spacecraft pose estimation is a process that comes with several difficulties, which arise from the fact that space environment is demanding and highly uncongenial for any equipment, which means that any existing equipment is likely to be less accurate or reliable in the space environment as it is in the earth's environment. Thus, the first significant issue is a lack of extensive and high-quality visual information [4]. Lack of adequate illumination at night or in outer space scenarios that involve faint light may affect the functionalities of the sensors such as cameras because the contrast of prominent features

becomes blurred. The high level of contrast in regions which are well illuminated and the rest which are in shade also poses a great problem in feature detection and thus poses estimation., micrometeoroids, cosmic rays, and orbiting space debris may interfere with an instrument's ability to acquire an accurate reading, blur the sensors, or inject noise right into the information collected, resulting in unwanted disturbance and noise when estimating the configuration. Another main issue is the necessity of developing computational efficient and real-time pose estimation algorithms [5]. These are systems in which computational power is generally low, and thus strict limitations are imposed on what kind of algorithms can be executed. Accurate determination of the pose is generally a complex implementation which often demands very complex mechanisms such as those that employ machine learning or superior filtration mechanisms which may be slightly complex. The problems are compounded by the requirement of extremely fast processing as any delay in pose estimation can lead to wrong navigation or mission failure. Moreover, spacecraft usually function in such conditions which are far from being static and often are characterized by rapidly changing positions and speeds of celestial bodies and other space vehicles. This makes the dynamic nature of the pose estimation a constant process hence making the algorithm to be complex. In certain situation such as proximity operations or docking the relative motion may be high and random and therefore the pose estimate needs to be very accurate and robust to avoid any collisions. Lastly, absence of ground data in space environment for testing of pose estimation algorithms also increases the challenge when it comes to developing and testing of these key systems [6].

### A. Modern Solutions for Spacecraft Pose Estimation

Many approaches have been used in the past to estimate the pose of spacecraft, which include, CNNs and RNNs, SLAM algorithms, Multi-Sensor Fusion, and Particle Filtering, however, the following challenges hinder the use of these methods in space. Different CNNs and RNNs, deep learning models, the latter need to extend large labeled datasets for learning that are hard to come by in space which is diverse and unpredictable. These models also do not generalize well to new situations or new inputs to the sensors that the car may encounter in practice and were not trained on. The most prominent and reliable algorithms of SLAM, when dealing with mapping and localization perform quite effectively, but can be grasping for computational resources and deteriorate performance in conditions where feature density is low or when the environment frequently changes. The main disadvantage of multi-Sensor Fusion is that it is severely affected by the quality of data received from each of the sensors of a system and the calibration parameters of the sensors, which might introduce some issues in the final results. Particle Filtering, while being more appropriate for the non-linear and/or non-Gaussian cases, can be time consuming and may have problems such as the particle depletion, where the algorithm starts to produce wrong estimates because of the lack of variety in the particle set. Such limitations mean that for reliable and accurate computation of the spacecraft pose, higher level and sophisticated techniques must be employed.

To address the limitations of outdated spacecraft, pose estimation methods, advanced techniques like Transformer Networks and Efficient Bayesian Optimization are being explored. In order to imaginatively integrate transformer to the entire learning satellite pose estimation task, a dual-channel transformers non-cooperative spatial object pose estimating networks is constructed. The satellites' orientation & geographical translation data are effectively separated by the dual-channel network architecture. To numerous different uses, optimization is being used successfully to tune machine learning parameters. When assessments are costly, as in the case of pose estimation, Bayesian optimization is also a useful strategy. Evaluation of optimization algorithms has demonstrated the latest developments in Bayesian optimization. When compared to other nongradient techniques like particle filters and evolutionary algorithms, Bayesian Optimization uses qualified guesses rather than spontaneous mutations and sampling, which reduces the number of iterations needed. Networks and Efficient Bayesian Optimization present a promising direction for developing more adaptive, precise, and robust spacecraft pose estimation systems, enhancing the safety and success of space missions.

### B. Key Contribution

Key Contributions are as follows:

- The research proposes a new Dual-Channel Transformer Model that utilizes EfficientNet for feature extraction to enhance flexibility and avoid overfitting as compared to traditional methods.
- A new approach involving 1×1 convolutions is introduced to turn the activation maps into inputs that are suitable with transformers for seamless integration convolutional features with the transformer architecture.
- The model uses two specialized subnetworks: a translation estimation subnetwork and an orientation estimation subnetwork, making use of quaternion-based activation functions to enhance pose prediction accuracy and robustness.
- Bayesian optimization using an UCB acquisition function and a Gaussian process is used in the research to optimize model parameters economically with a minimum number of evaluations.
- The method is verified with the Space Rendezvous Laboratory (SLAB) Kaggle dataset, exhibiting better pose estimation accuracy and optimization performance than existing methods, setting a new benchmark for pose estimation of spacecraft in challenging satellite imagery.

The research paper is structured to provide a clear and logical flow. It begins with an Introduction in Section I, followed by a review of existing methods in Section II. Section III defines the Problem Statement, leading into Section IV, which details the Proposed Dual-Channel Transformer Model and Bayesian Optimization Techniques. Section V presents the Results and Discussion, and the paper concludes with Section VI.

## II. Related Works

Accurate and reliable 6D pose estimate is necessary for on-orbit proximity activities like as debris collection, the docking process, and space rendezvous in a variety of illumination

scenarios as well as against a highly detailed history, such as the Earth. Proença and Gao [7] explores the use of photorealistic graphics and deep learning for monocular pose estimation for previously identified uncooperative spacecraft. First, describe URSO, an Unreal Engine 4 simulator that creates tagged pictures of Earth-orbiting spacecraft that can be utilized for neural network training and evaluation. Second, suggest modelling orientation uncertainty as an amalgamation of Gaussians using a deep learning model for posture prediction centered around orientations soft categorization. The ESA pose estimate problem and URSO datasets were used to assess this methodology. Our top model placed second on the real test set and third on the simulated test set during the competition. Additionally, our findings highlight the significance of several architectural and training elements and provide a qualitative example of how models trained on URSO databases might function on real-world images. Subsequent research endeavors ought to contemplate methods such as reducing the final layer connections to substitute dense connections that compromise efficiency. Furthermore, a specific network was used to generate outcomes for each dataset within this work. Having a similar backbone could be advantageous for both effectiveness and performance.

A novel deep neural network process that uses the temporal information during the rendezvous scenario to calculate a spacecraft's related posture. It makes use of LSTM components' capability to model data sequences and handle characteristics that are retrieved by a CNN backbone. Regression- Three distinct training methods are combined to produce superior end-to-end posture estimation and feature-based learning procedures that adhere to a coarse-to-fine funnelled strategy. By combining infrared thermal data alongside red-green-blue (RGB) inputs, CNNs' capacity to automatically extract feature representations from images is utilized to reduce the impact of artifacts during visible-wavelength space object imaging. The suggested framework called ChiNet has been verified on data from experiments, and each of its contributions is shown on a synthetic dataset. The strength of the design in non-nominal illuminating situations may be the subject of future research. In relation to spacecraft pose estimations, a different possible line of inquiry would be to address the issue of domain modification. This involves training a deep network via synthetic images and testing it on genuine information, the latter of which are usually hard to come by before the mission begins, however the earlier kind might be produced in huge quantities [8].

It has been suggested that the ability to estimate the pose of problematic objects in space is a crucial component for facilitating safe close-proximity activities, including active debris clearance, in-orbit maintenance, and space rendezvous. Conventional methods for pose estimation use Deep Learning (DL) algorithms or traditional computerized vision-based approaches. In this article, a unique DL-based approach for predicting the posture of recalcitrant spacecrafts using Convolutional Neural Networks (CNNs) is explored. Unlike other methods, the suggested CNN regresses poses directly, obviating the necessity for any pre-existing 3D information. Furthermore, the spacecraft's bounding boxes using the picture are anticipated in an easy-to-understand but effective way. The tests conducted show if this work interacts with the state-of-the-art in uncooperative spacecraft position estimation, which includes work needing 3D input and work that uses complicated CNNs to anticipate boundaries. [9].

For numerous space missions, including formations flying, rendezvous, the docking process, repair, and debris from space cleanup, spacecraft posture estimation is crucial. This Approach provide based on learning that uses uncertainty predictions to determine a spacecraft's attitude from a monocular picture. Firstly, cropped out the rectangle portion of the original image wherein only spacecraft were visible using a SDN. Subsequently, 11 pre-selected important points having clear features within the clipped image were detected and ambiguity was predicted using a keypoint detection network (KDN). To autonomously choose keypoints that possess greater detection precision from all identified keypoints, that provide a key location selecting approach. Using the EPnP technique, the spacecraft's 6D posture was estimated using these chosen keypoints. Research utilized the SPEED dataset to assess our methodology. Our approach works better than heatmap- and regression-based approaches, according to the studies, and the efficient uncertain predictions can raise the pose estimation's ultimate precision [10].

A real-time spaceship pose estimate technique by fusing the least-squares approach with a model using deep learning. With automated rendezvous docking and inter-spacecraft interaction, pose estimation in orbit is essential. Since deep learning algorithms are challenging to train in space, Research demonstrated that real-world trial outcomes may be predicted by software simulations conducted on Earth. This paper used a combination of DL and NLS to accurately estimate the pose in actual time given a single spacecraft photograph. To train a deep learning model, researchers built a virtual environment that can generate synthetic images in large quantities. The research presented here suggested a technique for using just synthetic photos for developing a DL model, a real-time estimating method with a visual basis that may be used in a flight testbed was built. As a consequence, it was confirmed that software models with the identical surroundings and relative distance could accurately anticipate the hardware outcomes of experiments. This work demonstrated an adequate application of a deep learning model learned solely on artificially generated images to actual images. Therefore, our study shod that the approach developed using just artificial information was suitable in space and provided a real-time pose estimate program for autonomous docking [11].

There have been a lot of recent study on the use of deep learning algorithms for space applications. Spacecraft posture estimate is a particular field where these algorithms are becoming more and more popular. This is because it is a basic need in numerous spacecraft navigation and rendezvous procedures. However, compared to terrestrial operations, the utilization of similar algorithms in space operations presents distinct obstacles. In the latter case, servers, powerful PCs, and shared assets like cloud services enable them. These resources are constrained in the space environment and ship, though. Therefore, an efficient and low-cost on-board predicting is needed to benefit from the above methods. Deep learning techniques for use in space were the subject of extensive research in the recent past. One arena wherein these methods are

gaining traction is spacecraft posture estimate, which is essential for many spacecraft rendezvous and navigational procedures. Nonetheless, the utilization of such algorithms in space operations poses unique challenges in contrast to how they are used in terrestrial operations. In the last scenario, servers, powerful PCs, and shared assets like cloud computing enable services to be provided. However, in space conditions and spacecraft, these resources are limited. Thus, in order to take use of these gets closer, an on-board inferencing that is both economical and power-efficient is required [12].

The drawbacks of the works concerning the pose estimation of a spacecraft are identified below. Most solutions leverage synthetic images in training deep learning models and hence may not be so effective when employed in real-world settings due to domain shift. Some methods involve the use of prior 3D information or intricate image texture and thus are limited due to unavailability of the information. Besides, they introduce many parameters in complex networks, thus reducing the real-time inference capacity and the practical applicability. The necessity of having a large number of synthetic images and real images for training can be time consuming with some sort of methods may work poorly under different illumination and high detailed backgrounds like Earth. Additionally, those methods not accounting for this uncertainty in key point detection and pose estimation may result in inferior solutions. Finally, it is very common not to have robust solutions adaptable to a large number of Space Craft arrangement and the operational settings.

## III. Problem Statement

Past research carried out to estimate the pose of the spacecraft has benefited significantly from deep learning and computer vision methods, however, it has left rooms for improvements in some areas such as the accuracy and the time efficiency extremely much more especially when undertaking the tests under different illumination conditions and also when dealing with uncooperative spacecraft [13] [14]. Previous approaches have issues with large computational costs, for example, it difficult for them to perform well under different lighting conditions, and pose uncertainties are not well addressed. To overcome these shortcomings, this proposed approach renders the following new approach that combines Transformer networks and Bayesian optimization. Thus, a new framework is proposed here to improve the accuracy and speed of pose estimation by applying the aptitude of Transformer models in dealing with the sequence data and in efficiently introducing the model parameters. This also aims at addressing some limitations posed by previous methods, such as weaker pose estimates, restricted applicability across various situations and until now called for poor real-time performance due to non-efficient and often unscalable solutions.

## IV. Proposed Dual-Channel Transformer Model for Spacecraft Pose Estimation and Bayesian Optimization Techniques

The suggested Dual-Channel Transformer Network along with Bayesian Optimization was selected for its better capability to process complicated satellite imagery and its efficiency in learning spatial as well as rotational features. As compared to conventional techniques which are plagued by excessive computational cost, poor generalization, and vulnerability to noisy or low-contrast data, our approach is better in terms of adaptability, real-time operation, and accuracy. This renders it extremely suitable for spacecraft pose estimation in harsh space environments. This choice is also substantiated by the limitations of current approaches such as CNNs, SLAM, and Particle Filters tend to have high computational requirements, poor generalization, and are very sensitive to noise or low-contrast images. These constraints limit their performance in dynamic or uncertain space environments, and they are less reliable for accurate and robust spacecraft pose estimation. The research process is guided by a systematic workflow to provide an efficient and accurate spacecraft pose estimation model. As shown in Fig. 1, the process starts with Data Collection, where raw images are acquired from sources like TRON authentic photos and synthetic datasets. The Creation of the Synthetic Dataset is essential in complementing real-world images and improving model training. The second step is Data Pre-Processing, wherein gathered images and synthetic images are refined to be rid of noise and to provide a uniform format for input. The processed data is then passed on to the Dual-Channel Transformer Model, utilizing EfficientNet for superior feature extraction. To further enhance model precision, Bayesian Optimization is utilized to optimize parameters, minimizing errors made through estimation and enhancing generalization. This end-to-end workflow increases the stability and efficiency of the model, allowing it to process intricate satellite images efficiently and perform sophisticated data analysis operations with great accuracy.

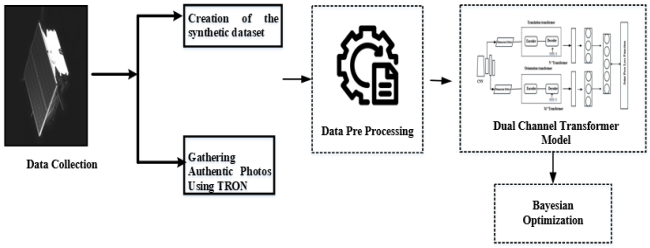


Fig. 1. Proposed figure.

### A. Data Collection

Research makes use of the dataset that Space Rendezvous Laboratory (SLAB) made available on Kaggle for their Satellite Pose Estimation Challenge. The training dataset comprises 12,000 artificial satellite images together with matching ground truth pose labels. There are 300 genuine photos and 2998 artificial images in the test dataset. The purpose of the genuine photographs, which differ significantly from the artificial ones, is to assess how well the posture estimation model and algorithm work with a real-world dataset. They were taken at SLAB using a Tango satellite mockup. Distribution of Synthetic and Real Images in Training and Test Sets is given in Table I.

TABLE I. Distribution of Synthetic and Real Images in Training and Test Sets

| Dataset | Synthetic | Real |
|---|---|---|
| Training set | 12000 | 5 |
| Test set | 2998 | 300 |

Every image offered has a 1920 × 1080-pixel resolution and is 8 bit monochrome. Using a high-definition texturing modeling of the Tango spacecraft from the PRISMA mission and a camera model of the Point Grey Grasshopper 3 camera with a Xenoplan 1.9/17mm lens (VBS), SLAB's Optical Simulator creates the synthetic photos. To simulate camera noise and depth of field, accordingly, Gaussian blurring and white noise are applied to every image. Some of the photos simulate scenarios in which the subject is photographed against a star field by having a black background. Real photographs of the Earth either completely or in part cover the background of the remaining pictures. The subsequent set of test images consists of real images that are sourced from SLAB's TRON facility. Utilizing a real Point Grey Grasshopper 3 camera equipped with a Xenoplan 1.9/17mm lens, TRON delivers photographs of a 1:1 mockup model for the Tango spacecraft of the PRISMA mission. Keep in consideration that the OS webcam emulators program uses the exact same camera. The locations and postures of the Tango spacecraft and the camera have been captured by calibrated motion-capturing cameras, and these data are utilized to determine the Tango satellite's ground truth pose in relation to the camera. We assess every algorithm's transferability between synthetic to real images using a test set of real images [15].

*1) Creation of the synthetic dataset:* The Optical Stimulator's camera emulator programs are used to produce the artificial visuals on the Tango spacecraft. The software creates photo-realistic pictures of the Tango spacecraft with the necessary ground-truth postures using an OpenGL-based image rendering process. 50% of the synthetic photos have random Earth photographs from the Himawari-8 geostationary meteorological satellite4 placed into the background of the image. The artificial light used for these photos is designed to most closely resemble the background of Earth visuals. The intersecting histogram curves of the image pixel intensities from both imageries show that the synthesized imagery produced by SPEED may nearly mimic the lighting levels recorded by the real flight photography. This shows off how much SPEED's image processing process has improved and how it can produce realistic, pose-labeled photos for any chosen spacecraft. [16]

*2) Gathering authentic photos using TRON:* Gathering authentic photos using TRON, the Tango spacecraft's actual photos were taken with SLAB's TRON facilities. Upon creating the images, the setup comprised a one-to-one replica of the Tango spacecraft along with a robotic arm with seven degrees of freedom fixed to the ceilings that supported the camera at its tip. A xenon short-arc lamp that simulates convergent sunlight in various orbital regimes and special LED wall panels that might simulate the dispersed lighting conditions brought on by Earth albedo are also features of the center. To get the ground-truth posture labels in the real photographs, ten Vicon cameras are employed to monitor the infrared markers between the evaluation camera and the space station replica. To eliminate any errors in the predicted targets and camera references frames, the meticulous calibration procedures described are carried out. In general, the calibrated Vicon system's autonomous posture assessment yields pose labels that have degree- and centimeter-level accuracy. The present efforts are being made to simultaneously combine readings from the robot and Vicon cameras to increase the ground-truth pose's accuracy by a few orders of magnitude. It should be noted that despite the fact which the two photographs have the same ground-truth positions and the Earth's albedo in overall, there are plenty of differences in the image characteristics which may be easily noticeable, including the texture, illumination, and eclipses of particular spacecraft elements [17].

### B. Data Preprocessing Steps

*1) Image loading and conversion:* The initial step in the data preprocessing pipeline involves the careful loading and conversion of the 8-bit monochrome images, which form the core of the dataset. These images, both synthetic and real, are stored in a format where each pixel's intensity is represented by a value ranging from 0 to 255, a typical range for 8-bit images. To begin, the images are loaded from the dataset using image processing libraries, ensuring that they are accurately read and stored in memory for further manipulation. Once loaded, the images are converted into a format that is more suitable for processing, such as NumPy arrays, which provide an efficient and flexible structure for handling large datasets in machine learning workflows. This conversion is essential as it allows for the application of various mathematical operations and transformations required during the preprocessing phase.

Among the steps of data pre-processing, the first and rather time-consuming one is loading and converting the 8-bit monochrome images on which the set is based. These images could be synthetic as well as real and are in a format in which the value of each pixel in terms of intensity can be in a scale of 0 - 255, which is a commonly employed format in ‘’8-bit’’ images. The first process in this case is the reading of the images from the dataset using image processing libraries, and the images are first preprocessed in that the images are brought into memory for further processing. After loading then they convert the images into a format that is easier to process, one of them being the NumPy arrays, which enhances the capability of large dataset input for use in most machine learning algorithms. This conversion is important because many different operations and transformations that are required at the preprocessing step are only possible with numerical data. To standardize invariant input, pixel intensity is scaled in all the images in the dataset. This is among other things done in an effort to standardize the pixel intensity values from their initial range of 0 to 255 to a range of 0 to 1. Normalization is a very crucial step for such reasons because it assists in bringing the pixel intensity into the similar ranges and in this way, not a single pixel intensity value will be overly influential during a training of the model. This way the input data is preprocessed in a way that is easier for the model to learn from the images hence improving performance and generalization that will be exhibited when the model is ran on another data set [18].

*2) Gaussian blurring and noise addition:* Gaussian blurring and noise addition are two major operations intending to improve the quality of synthetic images in the way that the synthetic imagery has faults that real data does not. The

Gaussian blurring is done by convolving each image with a Gaussian kernel and the standard deviation was set to 1 to smoothen the image but discard as well much of the high frequency noise. This blurring technique is fully realistic because it mimics factors such as depth of field and smoothed out of focus blurring that may be found inside actual camera systems to take off harsh edges and give synthetically produced images a more natural look. Further, to mimic the noise patterns of actually camera sensors, Gaussian white noise for enhancing the electrode signal to noise ratio is incorporated to the images. This noise that has a zero mean and a variance ($\sigma^2$) equal to 0 is defined as follows: 0022, adds additional small variations in pixel intensity that look like the phenomenon of shot noise, the kind of noise that arises from the nature of light. These adjustments are then used subtly to recreate a form of realism making the manufactured synthetic images to mimic natural response of real-world images which in effect enhances the model performances while on the testing phase [19].

*3) Background segmentation:* It is also necessary to define and divide the background of the images which can be background (black or Earth background) this operation is very important in order to separate the satellite from the background, which results in pose estimation improvement. Specifically for images with the Earth background, one needs to consider that the segmentation algorithm should be able to work with variation of the Earth's appearance and illumination

*4) Resize and cropping:* Before feeding them to the model, down sample the pictures to a more standardized size if that is required to minimize computational strain on the algorithm. When resizing make sure that the aspect ratio of the satellite is retained to avoid stretching of the satellite. Trim the pictures to the satellite, erasing everything else that might be around them or surrounding the satellite.

*5) Histogram matching:* This is done in order to align the intensity features of the two images and minimize the variations of illumination and contrast. This step normalises intensity distribution of synthetic images to that of real images, which is helpful when one uses transfer learning. This is particularly important since the histograms of curves of the synthetic images and the real images are nearly the same implying that they were both under the same illumination conditions. Fig. 1 Pre Processing steps are described in Fig. 2.

### C. Dual-Channel Transformer Model

The batch size has been set as B provided the satellite picture M∈R^(C×H×W). Following the EfficientNet extraction of features network, 2 layer of features P (t) and P (r), that have various rate sizes are chosen at random and allocated to each of the regressive sub networks. For converting activation maps into input that are suitable with transformers, must first convert is converted into P∈R^ (B×C×H×W) to (P)¨∈R^ (B×X×Y) accordingly, using 1×1 convolution in a dimension editor that follows its processing rules. The transformer's process stream is comprised of an encoding and a device for decoding.

Processed P∈R^(B×C×H×W ) to ( P)¨∈R^(B×X×Y )in order to translate activation maps into transformer-compatible input. The activating maps are flattened by the dimension editors using 1×1 convolution in accordance with their processing rules; P∈R^(B×C×H×W )is processed into P∈ R^(B×X_R×Y_R )accordingly. The encoder and decoder that make up a transformer's working flow is given in Eq. (1)

$$Z' = Decoder(Encoder(Z^{1-1}) \quad (1)$$

where Z^1 is the result of processing with numerous transformers, where Z^1 is handled as a one-dimensional sequenced feature S via the flattening layer after being produced by multiple-transformer analysis. In order to generate the pose information, next input S into the completely linked layer. The function that activates in the oriented regress networks is quaternion SoftMax-like. Dual-channel transformer model is shown in Fig. 3.

### D. EfficientNet Backbone Network

The new architecture of EfficientNet originated from the MBConv that integrated the SE system's attention mechanism. The SE module that was originally placed after deep convolutional layers describes how to refine feature responses using point-wise convolutional for the improvement of features., MBConv incorporates this idea at an earlier level where point-wise convolutions are applied to transform the dimensions of features before going deep convolution; thus, improving feature extraction with reduced computation. EfficientNet is therefore computationally efficient in feature extraction and high in performance from images. This is done sequentially, meaning that the model is trained progressively in terms of depth, width and resolution not exceeding a level that demands more computations which would slow down the system. The model's architecture also helps in getting faster training sessions owing to the lower computational demands of this network as opposed to other feature extraction networks. This efficiency is vital when working with large datasets of image features, for example, satellite images in which both the quality and the speed of the recognition are to be achieved [20]. Efficient Net Architecture is shown in Fig. 4.

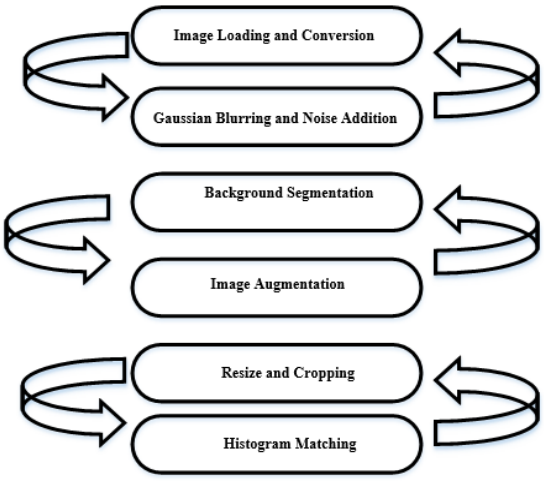


Fig. 2. Pre-processing steps.

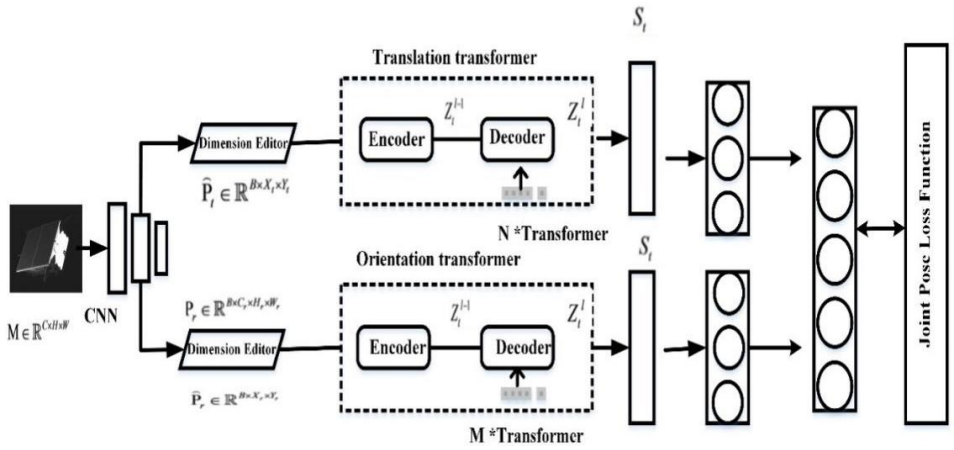


Fig. 3. Dual-channel transformer model.

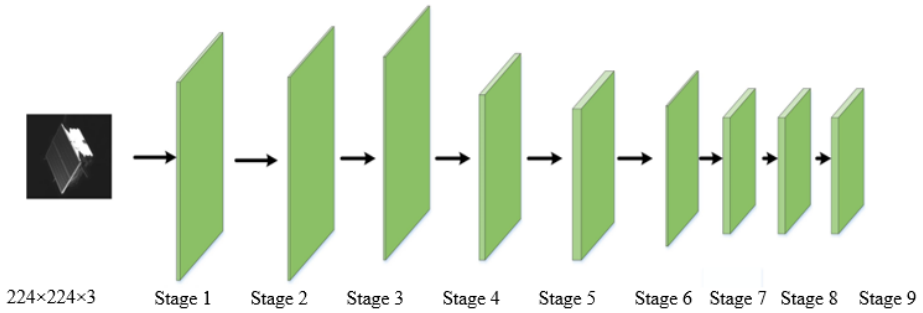


Fig. 4. Efficient net architecture.

Initially, having 32 convolutional layers of 3 × 3 × 3 with an initial phase size of 2 × 2, a feature map containing an input size of 224 × 224 × 3 is processed to yield 112 × 112 × 32 following normalizing and Swish function activation analysis. Following the initial processing, the features go through 16 distinct MBConv layers before being ultimately sized at 7 × 7 × 1280 Two feature layers are selected at random & fed into the translation transformers and the perspective transformers, two estimation of poses subnetworks, in the dual-channel transformers design.

*1) Feature layers and dimension editing:* The Feature Layers and Dimension Editing, thus, introduce the features extracted by the EfficientNet model into deformation ready for feeding to the Transformer. In particular, two feature maps named $P_t$ and $P_r$ are chosen from EfficientNet's output laying base for the next stage. These layers indicate different abstraction level in feature hierarchy, which means they have different sizes, and thus represent different resolution of the input data and are rich sets of inputs from which it is possible to extract features. They have to be transformed to be implemented within.

*2) Transformer model architecture:* A transformer is made up of multiple network blocks and an encoding and decoding unit. Positional encoding (PE), self-attention (SA), feed-forward network (FFN), residue relationship, normalization of layers (LN) blocks (Add & Norm), and multi-headed attention (MHA) are among its components. SA is the fundamental block of MHA. Transformers makes use of Add and Norm for enhanced model fitting, FFN to facilitate modelling learning, and MHA to connect diverse characteristics. Schematic diagram of the transformer structure is shown in Fig. 5.

*3) PE:* Preserving the spatial location data among each of the input image blocks is the primary goal of positional encoding. The features' positional is encoding is given in Eq. (2).

$$\begin{cases} PE_{(pos,2i)}=\sin(pos/10000^{2i/d}) \\ PE_{(pos,2i+1)}=\cos(pos/10000^{2i/d}) \end{cases} \quad (2)$$

In the given scenario, wherein PE is a matrix with two dimensions, the parameters sin and cos are positioned in its both even and odd terms, respectively. The a two-dimensional matrices is formed from variables such as sin and cos, and z^(l-1)has been encoded in positional.

*4) SA:* A key element of transformer is self-attention. By directing focus via a mathematical method, it replicates the properties that biological observing targets and collects features of particular important locations. The self-attention mechanism offers benefits in parallel processing, enhanced localized attention, and distant learning. The self-attention technique is primarily accomplished utilizing scaling dot-product focus, is given in Eq. (3).

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d}})\,V, \quad (3)$$

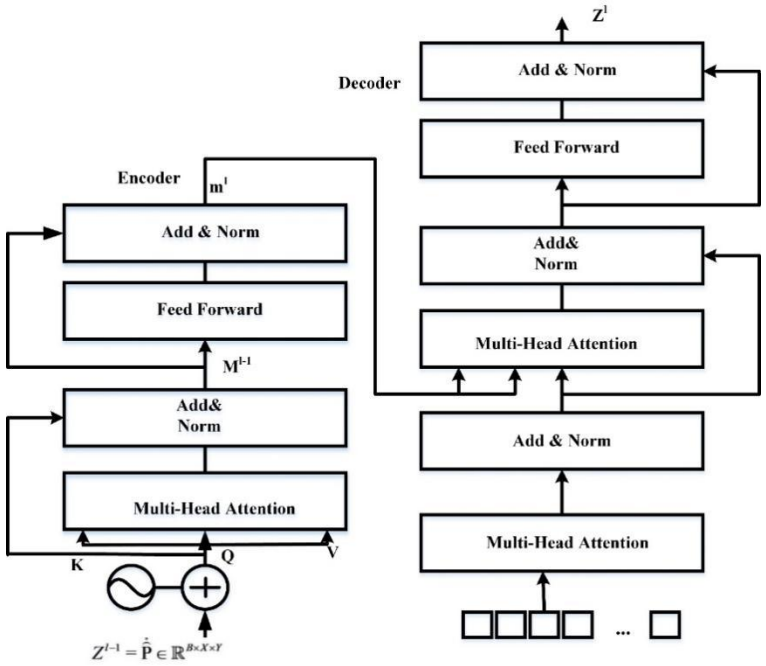


Fig. 5. Schematic diagram of the transformer structure.

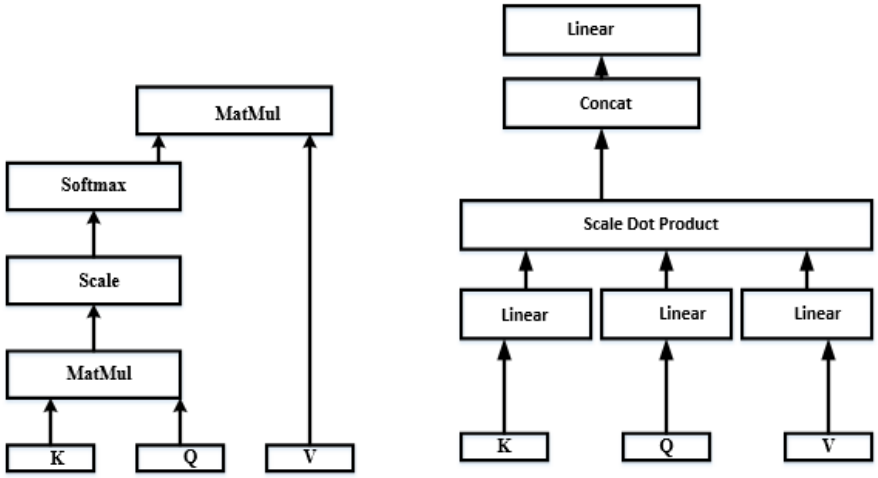


Fig. 6. Structure of a) SA module, b) MHA module.

where Q, K, and V represent the query matrix, key matrix, and value matrix, respectively, and d represents the input feature's dimensions. These are created by multiplying the matrix with the feature by 3 randomised weighting matrices. Structure of SA module and MHA module is shown in Fig. 6.

*5) MHA:* MHA is employed in a variety of projected areas to determine various projection information. The input matrix is then projected in various directions, and the resultant matrix is pieced together. SA is executed concurrently by MHA for every forecast outcome this is given in Eq. (4)

$$head_i = \text{Attention}\,(QW_i^Q, KW_i^Q, VW_i^V) \quad (4)$$

With $d_k = d_v = \frac{d_{model}}{h}$, denotes the total amount of heads are arranged, and $d_{model}$ denotes the total length of the given input feature. $d_k = d_v = d_{\frac{model}{h}}\ and$ indicates no of heads.

Concatenated the projected computation outcomes of numerous heads, is given in Eq. (5).

$$\text{MHA (Q, K, V)} = Concat\ (head_1, head_2, \ldots\ldots\ldots head_h)W^0 \quad (5)$$

Where in W^0∈R^( ⟦hd⟧ _(v×d_model ) ). Multi-head technology allows for the more detailed extraction of distinct heads' attributes. The feature extraction impact is better whenever the overall computation volume is equal to the value of a single head.

*6) FFN:* FFN maps features after a mapping from the high-dimensional space to the low-dimensional space. Incorporating various forms of information, improving the model's ability to solve problems, and removing low-resolution features by lowering the dimensionality are the objectives of mapping features to high-dimensional spaces. The method is derived in Eq. (6).

$$FFN(x)=\max(0,W_1 x+b_1)\,W_2+b_2 \quad (6)$$

where $W_1 \in R^{d_{model}}$and are the learnable weights, and b1 ∈ R4dmodel and b2 ∈ R4dmodel are the learnable biases.

Add & Norm: LN blocks and residual connections are contained in Add & Norm. The network depth's processing capability can be enhanced by the residual relationship, which can also successfully stop gradient expansion and the disappearance. LN accelerates the point of convergence of the mathematical framework by stabilizing the data feature distributions this is given in Eq. (7) and Eq. (8)

$$F(X) = LN(m^1 + m^{l-1}) \quad (7)$$

$$LN(x_i) = \alpha \times \frac{x_i - E(X)}{\sqrt{Var(x)+\epsilon}} + \beta \quad (8)$$

where α and β are the parameters that can be learned, and if their variance is zero, ε is used to avoid mistakes in calculation.

In the pose estimation subnetworks of the dual-channel Transformer model, two distinct regression subnetworks are employed to derive comprehensive pose information from feature maps. The first subnetwork is dedicated to estimating translation, or the position of objects, by analyzing spatial features extracted from the image. This involves regressing feature maps to predict the object's location. The second subnetwork focuses on estimating orientation, which involves predicting the object's rotation. For this task, a quaternion-based activation function is utilized, often resembling a SoftMax function but tailored to handle quaternion representations of rotation, providing a robust way to encode 3D orientations. Following the Transformer's processing, which enhances the feature representations through attention mechanisms and encoding-decoding processes, the resulting multi-dimensional output is flattened into a one-dimensional sequence. This flattened sequence is then fed into fully connected layers, which aggregate the information to produce the final pose estimates, including both translation and orientation of the object within the image. This structured approach allows the model to effectively combine and utilize the spatial and rotational data extracted from the satellite images [20].

*7) Bayesian optimization:* For the purpose of spacecraft pose estimation, Bayesian Optimization is used to fine-tune model learning rates, dropout rates, and the depth of Transformer layers to decrease pose estimation errors. The process starts with the formulation of objective function which measures the error involved in pose estimation which is the goal of the optimization process. Gaussian Process (GP) is employed to map the behavior of the objective function given a limited number of evaluations and yield a probabilistic estimate of the function mean and variance at locations in the design space yet unobserved. The Upper Confidence Bound (UCB) acquisition function then dictates which new set of parameters should be sampled in the next iteration with the intent of balancing exploration, where new parameters with a high level of uncertainty are chosen, and exploitation where parameters with a higher predicted reward is chosen. By indicating this iterative approach, it is possible to quickly navigate the parameter space and adaptively fine-tune the model's accuracy in terms of estimating a spacecraft's attitude and position with as few evaluations as possible to achieve the best result.

Bayesian Optimization uses qualifying guesses rather than spontaneous mutations and sampling, which reduces the number of repetitions needed. Utilizing a surrogate model that is fitted to every one of the prior specimens, the subsequent one to be evaluated is chosen in Bayesian optimization. Given the parameters, random uniform sampling is used to create an amount of starting samples. The surrogate model that is being utilized is a Gaussian process that is a non-parametric approach that builds a framework using all of the prior samples. A prediction's likelihood is also provided by the Gaussian process. As an acquisition function, the widely recognized Upper Confidence Bound (UCB) is utilized. As the name suggests, the subsequent parameter setting that is investigated is chosen based on the confidence bound above its present max. Bayesian Optimization is applied to enhance the pose estimation system by optimizing key parameters, specifically the feature radius and normal radius, which are fundamental to feature matching methods.

Fig. 7 depicts a parameter optimization procedure, where the process is initiated by the selection of 'p' training scenes, every scene comprising of 'm' objects that results in 'm*p' object detections. First, a parameter set is used for recognizing the objects (A) and then the result is assessed by scoring function (B). Afterwards, a Gaussian Process models the distribution of these performance results, which is denoted as C. According to this model the decision-making process chooses new sets of parameter for test (D). This is followed by the creation of the Gaussian Process with a selection of pre-specified number of parameter values and then applying Bayesian Optimization for 'n' steps. Lastly, all the 13 parameters and their assigned scores are employed to fit an extra Gaussian Process in order to determine expected optimum parameter set (E). This last stage supplements the identifications made on the best parameters by utilizing the acquired data to anticipate and determine the most profitable parameter setting.

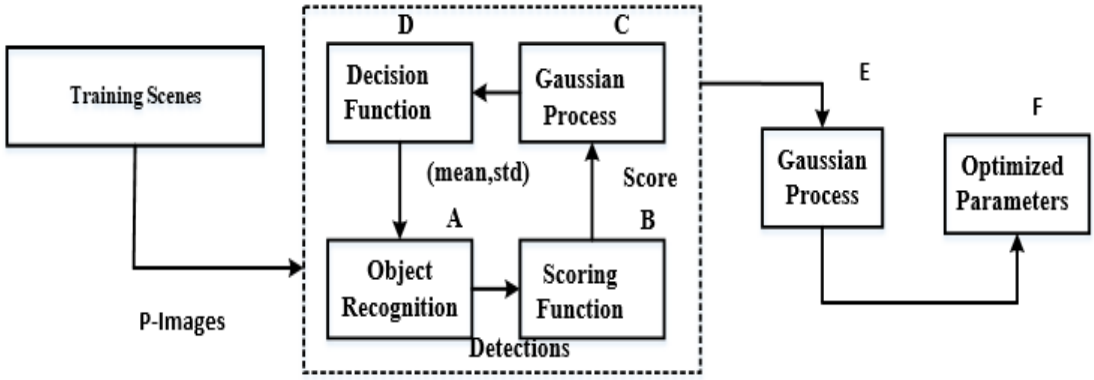


Fig. 7. Bayesian optimization for hyperparameter tuning in object recognition.

*8) Scoring the detections:* The outcome of the detection method's score to generate an additional score towards the optimization framework in order to maximize efficiency for reliable identifications. The system's overall score into TPs and FPs, or right and wrong findings, to obtain KDET P and KDEFP, accordingly. Any scoring mechanism may theoretically be employed in this situation, however the KDE is the result of the kernel density score during a pose given by the fundamental pose voting technique utilized for the estimation. Research employs the TP/FP ratio to calculate the score, rewarding high scores for accurate findings and penalizing higher scores for incorrect findings. For numerical causes, the score function is log-transformed since it produces more reliable results when the optimizing process is used in Eq. (9)

$$\text{score(KDE)} = \begin{Bmatrix} \log(\sum \frac{KDE_{TP}}{KDE_{FP}}) & i \sum KDE_{TP} \geq \sum KDE_{FP} \\ o, & \end{Bmatrix} \quad (9)$$

*9) Gaussian process regression for mode finding:* There is a chance of overfitting parameters for just the specific set of training scenes observed over training because just a tiny training set is utilized. This also utilize a Gaussian Process for regressing across the completed group of evaluations in order to reduce the possibility of incorrect parameter selection. This process makes the ideal parameter set prediction more accurate and smooth. To prevent overfitting of sparse training sets by Bayesian optimization techniques, alternative methods were additionally proposed. A term that penalizes steep peaks has been added to the newly acquired function. A Gaussian Process is then fitted to all examined sites in order to identify a stable maximum. The matrix made up of the variables X and the final score y can be used to represent the total amount of investigated points, or n this is given in Eq. (10)

$$x, y = \left\{ \left( x_i f(x_i) \right) \ | i = 1, \ldots \ldots n \right\} \quad (10)$$

A distribution is necessary in order to use a Gaussian Process for predicting the predicted result at new values for parameters. In this case, ˆx represents a brand-new, unproven parameter set this is given in Eq. (11).

$$\begin{bmatrix} y \\ x \end{bmatrix} \sim \begin{bmatrix} K & K_x^T \\ K_x & K_{xx} \end{bmatrix} \quad (11)$$

When K is the covariance matrix provided by a chosen kernel, k(x1, x2), and each index is determined by the interaction of a pair of parameters. Thus $K_{nxn,}$ $K_{nx1,}$ ) is obtained. to determine the new parameter's predicted value, which is determined by the difference between the variance and the mean.

By using the mean and the range to represent the degree of uncertainty, determine the anticipated amount of the newly added parameter this is given in Eq. (12) and Eq. (13)

$$E(x) = K_x K^{-1} \text{y} \quad (12)$$

$$var(x) = K_{xx-} K_x K^{-1} K_x^T \quad (13)$$

In this case, the kernel function K requires a distance d as inputs, integrating the Matern covariance $C_V$ and the diagonal noise terms N. This adds an additional term into the covariance functioning, which when combined with the Bayesian Optimization yields a Matern-kernel as well as a White Noise kernel, making the Gaussian process less susceptible to noises this is given in Eq. (14).

$$K(d) = C_V(d) + N(d) \quad (14)$$

The function is represented by J, and the gamma function is denoted by Γ. Since the entire dataset is not utilized, the white noise increases the evaluation's uncertainty this is given in Eq.. (15) and Eq. (16).

$$C_V(\text{d}) = \sigma^2 + \frac{2^{l-v}}{\tau(v)} \left( \sqrt{(2v\frac{d}{\rho})^v} j_v((2v\frac{d}{\rho}) \right) \quad (15)$$

$$N(d) = \begin{Bmatrix} \sigma, & if\ d = 0 \\ 0, & otherwise \end{Bmatrix} \quad (16)$$

The equation provided seems to define a kernel function, $N(d)$ where d represents some distance measure, and the kernel takes the value σ sigma when d=0 otherwise. This kernel is used to construct the covariance matrix for a Bayesian optimization process. The parameters must be established prior the prediction may prove computed, even though this kernel is utilized to produce the covariance matrix. is used to do a minimization procedure which fixes the v value, or the amount that distant points interacts with the projected result, whereas fitting the parameter values to the known score y. That will

provide a more accurate parameter forecast. These variables allow for the calculation of the kernels and the creation of an additional durable function given the expected parameter space. Numerous samples have been obtained and the space of parameters is investigated utilizing Bayesian optimization utilizing the training information and the scoring system [21]. Flowchart for Bayesian optimization is shown in Fig. 8.

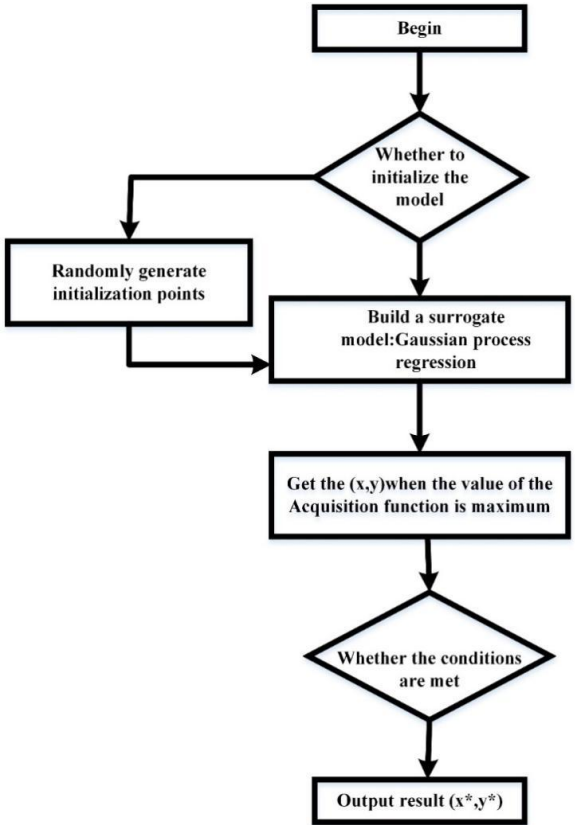


Fig. 8. Flowchart for Bayesian optimization.

```
# Pseudocode for Bayesian Optimization with Gaussian Process Regression
Start: Initialize the problem
Define the objective function f(x) to be optimized
Define the parameter space X (e.g., feature radius, normal radius)
Initialize Gaussian Process with a chosen kernel (e.g., Matern kernel)
Initialize acquisition function (e.g., Upper Confidence Bound - UCB)
n_initial_samples = 10
X_initial = RandomUniformSampling(X, n_initial_samples)
y_initial = EvaluateObjectiveFunction(f, X_initial)
GP = FitGaussianProcess(X_initial, y_initial)
n_iterations = 100
for i in range(n_iterations):
X_next = SelectNextSample(GP, X, acquisition_function="UCB")
y_next = EvaluateObjectiveFunction(f, X_next)
X_initial.append(X_next)
 y_initial.append(y_next)
 GP = FitGaussianProcess(X_initial, y_initial)
Log or print the best result so far
   BestX, BestY = GetBestResult(X_initial, y_initial)
   print(f"Iteration {i+1}: Best X = {BestX}, Best Y = {BestY}")
Output the final optimal parameters and corresponding score
OptimalX, OptimalY = GetBestResult(X_initial, y_initial)
print(f"Optimal Parameters: {OptimalX}, with score: {OptimalY}")
End
```

## V. Result and Discussions

This research presents a novel breakthrough in spacecraft pose estimation by combining deep Transformer networks with Bayesian Optimization algorithms. The suggested Dual-Channel Transformer Model, augmented with EfficientNet-derived feature layers, is shown to exhibit higher accuracy in pose estimation than traditional approaches. Through the use of Bayesian Optimization, the model efficiently optimizes essential parameters like learning rates and network depths, making use of Gaussian Process Regression and Upper Confidence Bound (UCB) in order to reduce pose estimation error. The performance of the model is strictly verified using the Space Rendezvous Laboratory (SLAB) dataset, achieving significant improvements in both translational and rotational accuracy. The findings showcase a notable decrease in position and attitude errors under different distances, enhanced reliability in actual spacecraft pose estimation applications, and optimized parameters for the model that increase both efficiency and accuracy. This novel method sets a new standard for spacecraft pose estimation, proving effective in processing complicated satellite imagery and enhancing overall model performance.

### A. Performance Evaluation

*1) Localization Error (Translational Error):* This measures the Euclidean distance among the foretold and ground-truth positions in 3D space (X, Y, Z). The formula for localization error is given in Eq. (17).

$$\sqrt{(x_{pred-}x_{true}{}^{2}) + (y_{pred-}y_{true}{}^{2}) + ) + (z_{pred-}z_{true}{}^{2})} \quad (17)$$

Where $x_{pred,}$ $y_{pred,}z_{pred,}$ are the predicted coordinates, and $x_{true,}$ $y_{true,}z_{true,}$ are the ground-truth coordinates.

*2) Orientation Error (Rotational Error*)**:** This measures the angular difference between the predicted and ground-truth orientations, typically represented by quaternions or Euler angles. The rotational error in degrees can be computed in Eq. (18).

$$Orientation\ Error = \cos -1(2(\ q_{pred}.q_{true})^{2} - 1 \quad (18)$$

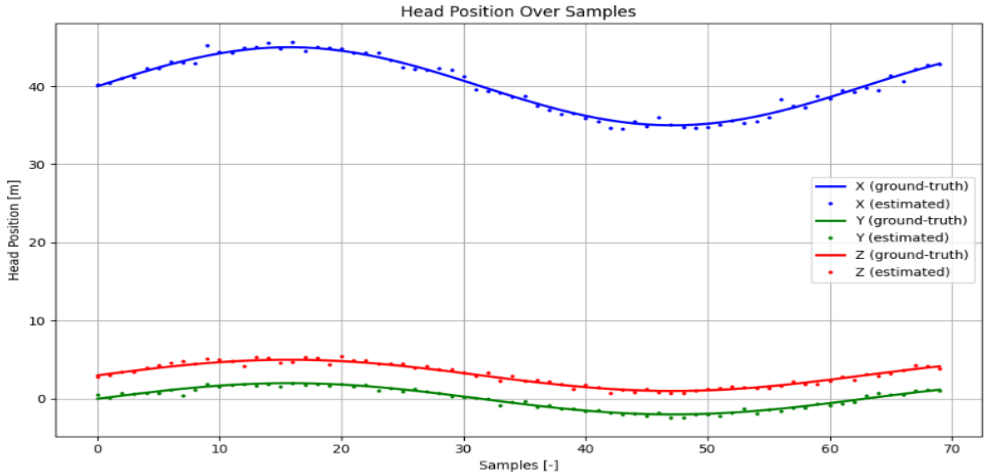


Fig. 9. Head position over samples.

Fig. 9 illustrates the comparison between ground-truth and estimated head positions across X, Y, and Z coordinates over several samples, with solid lines depicting ground-truth and dashed lines showing estimated positions. The blue, green, and red lines correspond to the X, Y, and Z coordinates, respectively. This visualization is key for assessing the accuracy of head position estimation algorithms, particularly in motion tracking and virtual reality applications. A close alignment between the ground-truth and estimated lines suggests that the estimation algorithm performs with high accuracy, effectively mirroring the true head movements across all three dimensions.

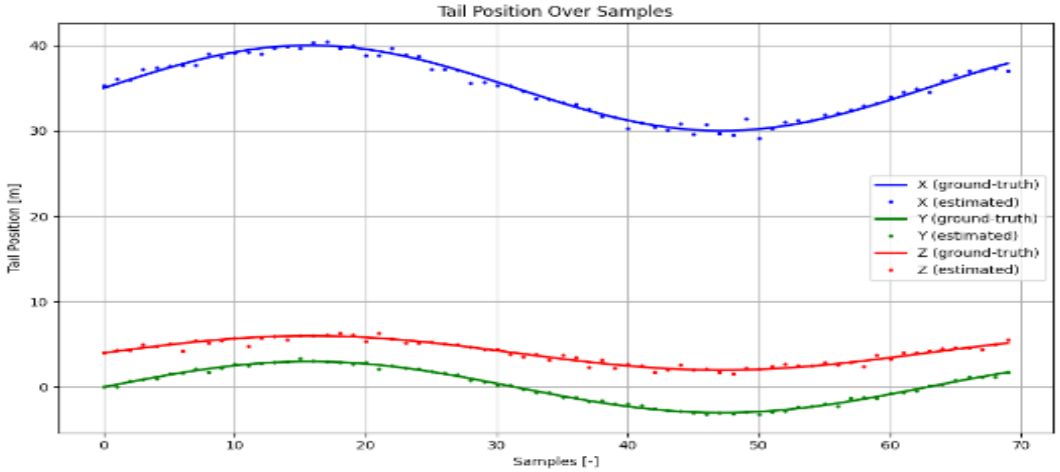


Fig. 10. Tail position over samples.

Fig. 10 shows the comparison between the ground truth and estimated tail positions in three dimensions (X, Y, Z) over a series of samples. The x-axis represents the sample number, ranging from 0 to 70, while the y-axis represents the tail position in meters, ranging from -20 to 40. The blue, green, and red dots indicate the actual measured positions for X, Y, and Z respectively, while the smooth curves in corresponding colors represent the estimated positions. t is probable that this graph is used to assess the error of tracking or predicting algorithm where one would plot the estimated position against the time and the plotted position against the actual measured position against time.

Fig. 11 shows the position error of the spacecraft's center of mass (CoM) over time across three axes: X, Y, and Z. The position error indicates how much the spacecraft's actual position deviates from its position. The x-axis signifies the number of samples (time), while the y-axis shows the position error in meters. The blue, green, and red lines correspond to the X, Y, and Z axes, respectively. The y-axis showing the error in meters (ranging from -2 to 3 meters) and the x-axis showing the number of samples (from 0 to 70).

Fig. 12 represents the change of the attitude error of a spacecraft's center of mass over time. Attitude in spacecraft pose estimation means the orientation of the spacecraft in space. The attitude error shows the difference of the actual orientation with the required degrees of orientation. The value on the horizontal axis is that of sample number with the values ranging from 1 to a figure slightly below 70. The y-axis represents the ˜attitude error' in degrees scale with the range of roughly 2 to 8 degrees. On the graph presented below, the changes in the attitude error can be observed with clear elevation and decline periods. This variability implies fluctuations of the stability or the control system performance of an object.

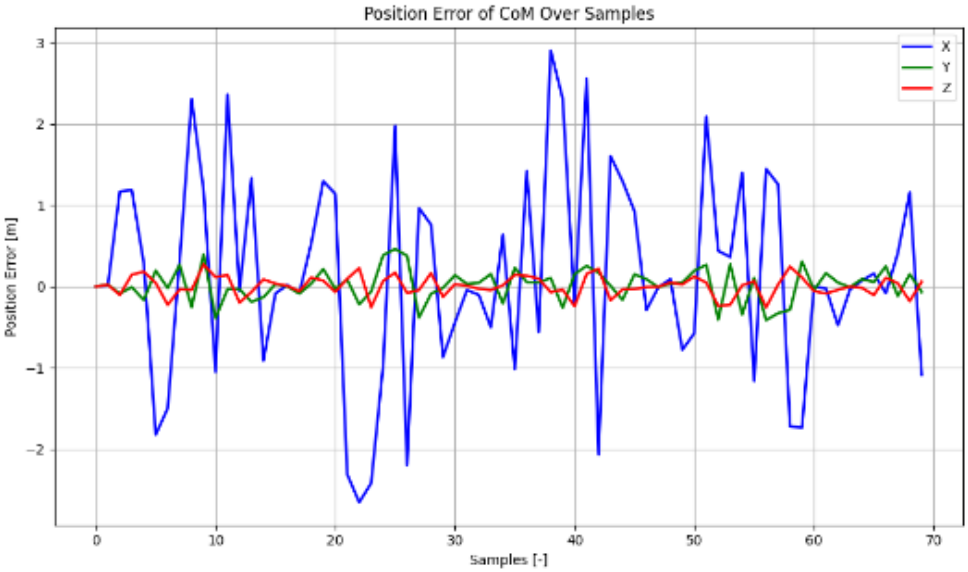


Fig. 11. Position error of CoM.

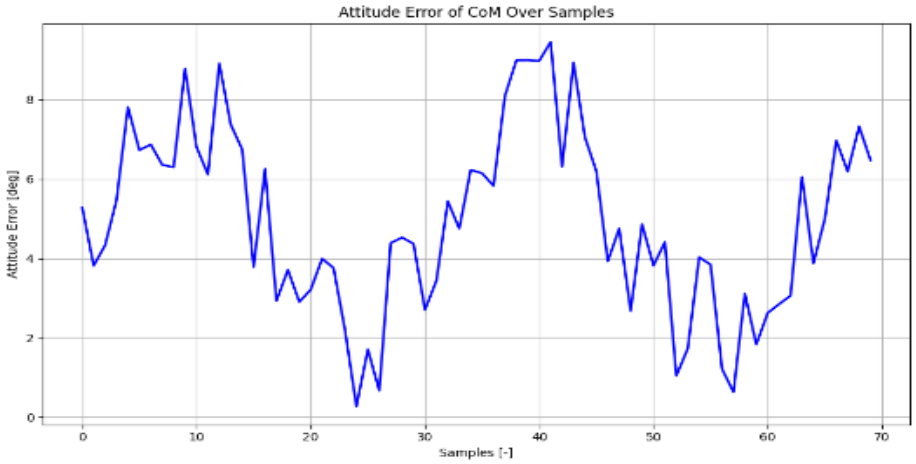


Fig. 12. Attitude error of CoM over samples.

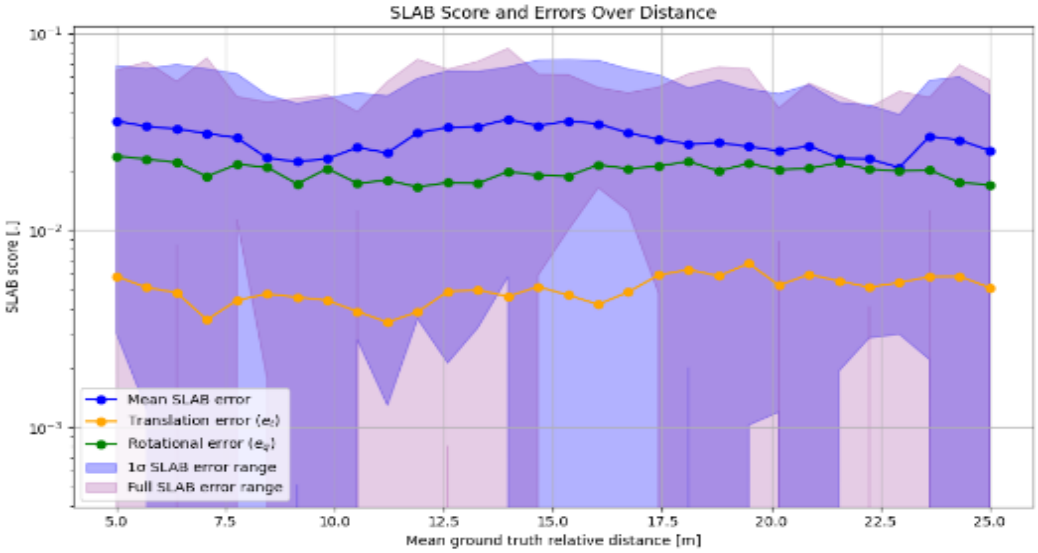


Fig. 13. SLAB Score and errors over distance.

Fig. 13 shows how distances affect pose estimation errors of spacecrafts the range of distances is shown on the horizontal axis, while the vertical axis describes SLAB scores in logarithmic degrees. The blue line represents the Mean SLAB Error, meaning that it presents the mean pose estimation errors. The green line represents Translational Error which is exclusively related to the errors of spacecraft's movement. The dark blue line with circle markers represents Rotational Error. The orange line gives the Full of SLAB Error Range to get the overall idea of errors. Grey-shaded areas in light purple and orange represent error variability, including the full range of SLAB error range, as well as 1σ SLAB error bars. This graph is important as it depicts the manner in which the accuracy and reliability of pose estimate are impacted by the distance from the spacecraft to its object.

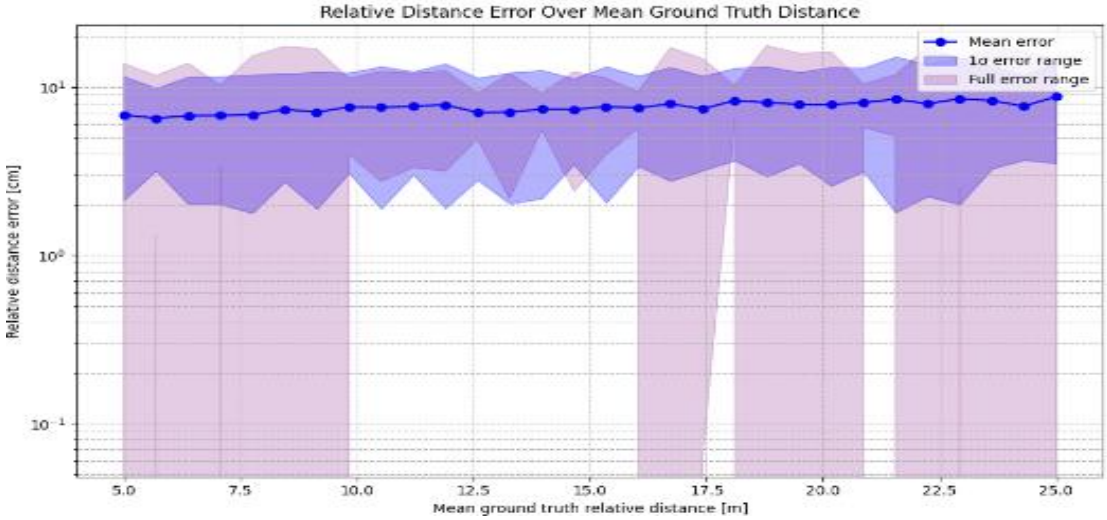


Fig. 14. Relative distance error over mean ground truth distance.

Fig. 14 shows the accuracy rates of the estimation of the position of a spacecraft at different distances. The horizontal axis depicts the average ground truth distance in meters (0 – 25 meters) while the vertical axis depicts the relative distance error in log-log scale in centimeters where values ranges from 0. 01 centimeters to 10 centimeters. The solid blue curve presents the average error and despite the increase of distance this value does not change dramatically. The region between this line and the light purple colored area is the distribution of data within one standard deviation (1σ Error Range) and the darker colored area represents the range of errors observed which is the maximum and minimum. This graph is needed for determining the accuracy of the spacecraft pose estimation, especially during essential operations such as docking or landing, as the nature of error dependence on distance can be observed from this graph.

Fig. 15 shows how accurately a spacecraft's orientation can be determined over varying distances. The mean error line shows the average deviation from the true pose, while the 1σ error range and full error range illustrate the variability and extremes of these errors. This helps in assessing the reliability and precision of the pose estimation system, which is vital for navigation, docking, and other critical operations in space missions. By analyzing the Attitude Error Analysis Based on Ground Truth Distance pose of a spacecraft, the Relative Attitude Error Over Mean Ground Truth Distance is important to know how well orientation measurements of a spacecraft can be from far and near. The mean error line was used to indicate the average distance off true pose, while the 1σ to demonstrate the spread of these errors and full error range shown the overall high/low of these errors.

Table II evaluates four object detection methods based on their Intersection over Union (IOU) scores, orientation errors $\xi_R$and localization errors $\xi_T$The SPN method exhibits moderate IOU scores but shows relatively high orientation and localization errors, indicating less accuracy in detecting object positions and orientations. HRNet+PE excels with the highest IOU scores and the lowest errors in both orientation and localization, reflecting superior precision and accuracy. URSONet presents lower IOU scores and significant errors in orientation and localization, suggesting lower overall performance. The Proposed method combines high IOU scores with competitive orientation and localization errors, indicating a well-balanced approach with effective accuracy and precision in object detection.

### *B. Discussions*

The present research offers a revolutionary method to spacecraft pose estimation through the implementation of a Dual-Channel Transformer Network coupled with Bayesian Optimization, providing a crucial improvement over other conventional methods such as CNNs, SLAM, and Particle Filters. With the use of EfficientNet to achieve stable feature extraction and splitting translation and orientation predictions using specific subnetworks, the model is able to capture both the spatial and rotational features of spacecraft from challenging satellite images [25]. Employment of Bayesian Optimization in tandem with Gaussian Process Regression and UCB acquisition fine-tunes the model through optimized hyperparameters via low-order evaluation, raising the bar of both accuracy and computation. Demonstrated on the SLAB data, the solution worked with far superior generalizability and precision in a multitude of scenarios and exemplified potential deployment in actual operational autonomous space settings. In comparison to

current research, this work not only obtains better estimation performance but also proposes a more scalable and flexible method. Outcomes bridge gaps in literature by offering solutions to the most critical challenges of domain shift, computational expense, and sensor noise sensitivity, building a strong platform for future development in deep learning-based space navigation and robotics.

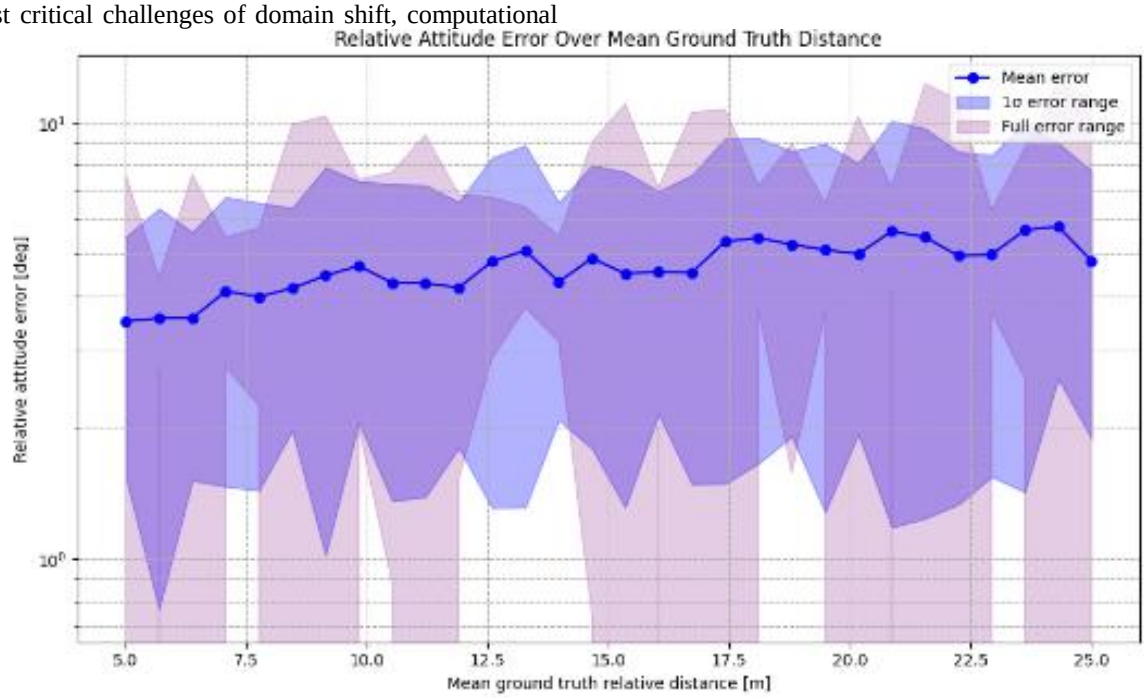


Fig. 15. Relative attitude error analysis based on ground truth distance.

TABLE II. PERFORMANCE COMPARISON OF OBJECT DETECTION METHODS: LOCALIZATION AND ORIENTATION ERRORS

| Method | Mean IOU | Median IOU | Mean $\xi_R$ (degree) | Median $\xi_R$ (degree) | Mean $\xi_T$ (m) | Median $\xi_T$ (m) |
|---|---|---|---|---|---|---|
| SPN [22] | 0.8582 | 0.8908 | 8.4254 | 7.0689 | 0.2937 | 0.1803 |
| HRNet+PE [23] | 0.9534 | 0.9634 | 0.7277 | 0.5214 | 0.0359 | 0.0147 |
| URSONet [24] | | | 3.1036 | 2.6205 | 2.1890 | 1.2718 |
| Proposed | 0.9610 | 0.9727 | 0.6812 | 0.5027 | 0.0320 | 0.0144 |

## VI. CONCLUSION AND FUTURE WORK

This is a novel research and innovation in the field of spacecraft pose estimation which utilizes Dual-Channel Transformer Model with EfficientNet is as feature extractor and Bayesian Optimization is used for hyperparameters tuning. The proposed method has shown a clear advantage in terms of translational and rotational accuracy over traditional methods. EfficientNet made the model able to comprehend complex spatial and rotation characteristics of the spacecraft, while dual subnetworks focusing on translation and orientation contributed to improved pose estimation accuracy. Bayesian Optimization as an optimization algorithm using Gaussian Processes with Upper Confidence Bound (UCB) acquisition function enabled adequate hyperparameter tuning, with a reduced number of function evaluations. Results obtained by validating this new approach on SLAB dataset shows significant improvement regarding position and attitude estimation for different distances, confirming advantages presented by this innovative concept in real-world applications. Even though the progress achieved, several directions should be further explored. First, more diverse data should be used to establish a model with stronger generality. Data from different types of spacecrafts under various environmental conditions need to be included in the training and testing datasets to improve the generality of the proposed method and verify its effectiveness under more general settings. Real-time learning can also be integrated into the model so that onboard or native spacecraft climate data can be continuously accumulated to update (train) the current deep learning models during missions. This would make it feasible for the long-duration application of a deep-learning-based model in varying space environments. Hybrid optimization algorithms such as coupling Bayesian optimization with genetic algorithms or reinforcement learning could potentially enhance both computational efficiency and modeling accuracy. Furthermore, expanding this work from attitude estimation to other applications, including velocity estimation or fuel efficiency optimization and control, will significantly increase our capability in exploring state-of-the-art technologies using attitude as well as other critical information in modern autonomous navigation tasks of docking, rendezvous and landing. This work establishes a new state-of-the-art for spacecraft pose estimation, but continued advancements in adaptability, real-time learning, and more extensive parameter estimation should allow even higher levels of accuracy and efficiency for spaceflight missions.

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# Energy-Efficient Cloud Computing Through Reinforcement Learning-Based Workload Scheduling

Ashwini R Malipatil[1], Dr M E Paramasivam[2], Dilfuza Gulyamova[3], Dr.Aanandha Saravanan[4], Janjhyam Venkata Naga Ramesh[5], Elangovan Muniyandy[6], Refka Ghodhbani[7]*

Assistant Professor, Department of Computer Science and Engineering, BNM Institute of Technology, Bangalore, India[1]
Associate Professor, Department of ECE, Sona College of Technology, Salem, India[2]
Computer Engineering Department, University of Information Technologies in Tashkent, Tashkent, Uzbekistan[3]
Professor, Department of ECE, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, India[4]
Adjunct Professor, Department of CSE, Graphic Era Hill University, Dehradun, 248002, India[5]
Adjunct Professor, Department of CSE, Graphic Era Deemed to be University, Dehradun, 248002, Uttarakhand, India[5]
Department of Biosciences-Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences, Chennai, India[6]
Applied Science Research Center, Applied Science Private University, Amman, Jordan[6]
Center for Scientific Research and Entrepreneurship, Northern Border University, 73213, Arar, Saudi Arabia[7]

***Abstract*—The basis for current digital infrastructure is cloud computing, which allows for scalable, on-demand computational resource access. Data center power consumption, however, has skyrocketed because of demand increases, raising operating costs and their footprint. Traditional workload scheduling algorithms often assign performance and cost priority over energy efficiency. This paper proposes a workload scheduling method utilizing deep reinforcement learning (DRL) that adjusts dynamically according to present cloud situations to ensure optimal energy efficiency without compromising performance. The proposed method utilizes Deep Q-Networks (DQN) to perform feature engineering to identify key workload parameters such as execution time, CPU and memory consumption, and subsequently schedules tasks smartly based on these results. Based on evaluation output, the model brings down the latency to 15 ms and throughput up to 500 tasks/sec with 92% efficiency in load balancing, 95% resource usage, and 97% QoS. The proposed approach yields improved performance in terms of key parameters compared to conventional approaches such as Round Robin, FCFS, and heuristic methods. These findings show how reinforcement learning can significantly enhance the scalability, reliability, and sustainability of cloud environments. Future work will focus on enhancing fault tolerance, incorporating federated learning for decentralized optimization, and testing the model on real-world multi-cloud infrastructures.**

***Keywords*—Cloud computing; energy efficiency; reinforcement learning; virtual machine; workload scheduling***

## I. INTRODUCTION

Cloud computing technology has emerged as essential technology because it provides adaptable and effective computer resources to all individuals together with enterprises worldwide. Cloud services provide instant access to processing power and storage and networking capabilities which has led to a total transformation of various business operations. Since this transition occurred companies can carry out innovation and growth at rapid speeds [1]. The expansion of cloud service use raises the electricity consumption in major data center facilities [2]. This challenge has become somewhat important as meeting the demand for energy, without losing performance in cloud-based services is a problem. Data centers form the foundation of cloud computing today. Computing, Storage, and Networking are the functions in data centers. They consume much electricity [3]. This increase in workload in the data centers due to the ever-increasing demand for cloud-based applications has seen energy consumption significantly shoot up. Most of the power consumed by the data centers can be traced to the need to process complicated workloads and maintain cooling and networking operations, thus ensuring cloud services are always functioning [4]. Therefore, the reduction of the energy footprint of cloud computing has become both a technical and environmental imperative. Optimization of energy usage in cloud data centers is a concern not only to reduce the cost of operation but also as an urgent environmental need. The achievement of maximum efficiency requires workloads to have effective scheduling algorithms. This system will enable resource management and minimal energy usage to achieve efficient operation and cost-effectiveness for cloud data centers [5].

The actual practice of workload scheduling requires dispersing computational workloads onto virtual machines to achieve minimum usage of power and resources. Cloud infrastructure performance and operational expenses improve through scheduling optimization leading to better operation. The majority of traditional scheduling approaches present limited interest in energy conservation because they focus on two separate objectives: peak performance and cost reduction. Cloud computing presents great challenges in workload management since user needs vary frequently and deployment options differ widely and service-level agreements are strictly enforced in this environment where workloads exhibit unexpected dynamism and extreme resource variability [6]. Fixed scheduling techniques and those following rules fail to manage operational modifications in real-time which leads to poor resource distribution together with increased energy consumption. The research recommends using reinforcement-learning algorithms for scheduling problems in cloud environments.[7]. The demand for adaptive scheduling approaches which minimize power

usage without affecting system performance remains immediate [8], Systems that run through the cloud have the ability to improve their energy efficiency without jeopardizing either their reliable service level or performance standards through this approach [9].

The framework enables system learning through environment interactions because of its reinforcement learning capabilities. The optimal scheduling policy through interaction with the technique has potential for workload scheduling by leveraging the environment to teach optimal scheduling policies. In reinforcement learning, an agent acts in response to its perception of the environment and is rewarded or punished appropriately. It lets the agent learn to improve with time in such a manner that it learns from the outcome of its actions [10]. Using RL for scheduling workload in the cloud, an indirect resource allocation can be made on the fly according to the real-time demands and thus energy consumption optimizes continuously. Unlike previous heuristic-based methods, these methods will not depend on predefined rules but learn from previous experiences and hence, can handle very dynamic and complex cloud environments [11]. This adaptability pays off well in cloud computing, where changes in workload characteristics can be rapid, requiring real-time resource allocation on the fly. In this study, the focus is primarily on using algorithms based on RL to schedule cloud workloads, with the purpose of minimizing energy consumption while respecting performance standards. Through reinforcement learning, this study will describe and apply the strategy that optimizes the pursuit of energy efficiency within cloud infrastructures. For reducing energy consumption without compromising its overall performance within cloud services, we suggest an RL-based task scheduling algorithm that adjusts to changing system conditions and workload demands [12]. The proposed method integrates reinforcement learning with energy-aware scheduling techniques, which enables dynamic adjustments to workload distribution based on real-time energy consumption data. This will help cloud computing infrastructures become more sustainable by incorporating feedback loops and making adjustments to scheduling policies based on past performance. The rest of the paper focuses on the design, implementation, and evaluation of the effectiveness in bringing down the energy consumption while ensuring high service reliability for the RL-based scheduling algorithm [13]. This research contributes to the emerging area of energy-efficient cloud computing by introducing a new approach for optimizing energy usage in cloud data centers using reinforcement learning techniques.

The major key contributions are as follows:

*1)* It introduces a reinforcement learning-based algorithm for optimal energy-efficient scheduling of workloads in cloud environments.

*2)* The scheduler adapts strategies in real-time to manage unanticipated cloud workloads while optimizing energy consumption.

*3)* It balances optimization of energy consumption with QoS constraints to satisfy SLA requirements and system dependability.

*4)* To validate the proposal, the presented method is tested against traditional algorithms such as FCFS, RR, and heuristic-based algorithms with better energy efficiency and performance.

*5)* It ensures scalability across different cloud infrastructures and hence is applicable to various real-world cloud service providers.

The following is the remaining part of the section is structured: Section II as Related works on previous papers, Section III as problem statement, Section IV as proposed methodology, Section V as result and discussion and Section VI as conclusion and future work is provided.

## II. Related Works

Mobula et al. [14] proposed a new approach to address the challenges of workflow scheduling in the cloud environment by focusing on the optimization of energy efficiency while satisfying user-defined constraints such as deadlines and budget. Acknowledging that workflow scheduling is an NP-complete, they proposed two algorithms called Structure-based Multi-objective Workflow Scheduling with an Optimal instance type and Structure-based Multi-objective Workflow Scheduling with Heterogeneous instance types. The SMWSO algorithm computes the optimal instance type and the number of virtual machines that should be required to improve the scheduling efficiency. In the meanwhile, SMWSH extends this concept by adding heterogeneous VMs that allow greater flexibility in a diverse cloud environment. Their research work emphasizes the critical role workflow structures play in making scheduling decisions and proves that optimized instance types and VM allocations can significantly decrease energy consumption. Based on simulations, their methods obtained superior heir result manifests the relevance of using workflow-aware scheduling strategies in cloud environments, especially in cost reduction and sustainability. Their work serves as a basis for further research into intelligent workload scheduling strategies that integrate optimisation techniques to improve cloud computing infrastructures.

Murad et al. [15] proposes an Optimized Min-Min (OMin-Min) task scheduling algorithm for enhancing cloudlet scheduling and resource allocation. This study is hoped to increase the performance of a system by increasing resource utilization and decreasing task execution time. The OMin-Min, which is the enhanced version of the traditional Min-Min, is constructed by applying these approaches, and the performance of OMin-Min is compared to that of the Min-Min, Round Robin, Max-Min, and Modified Max-Min algorithms. The experiments include different sizes of cloudlets (small, medium, large, and heavy) on three scientific workflow datasets: Montage, Epigenomics, and SIPHT.The evaluation and implementation are performed using the CloudSim simulator within a Java environment. The merits of the new algorithm are in its capacity to generate optimal scheduling outcomes, provide lower completion times, and ensure improved resource utilization, ultimately contributing to better throughput. However, the limitation might be based on the computational difficulty of optimal scheduling decisions for large-scale or extremely dynamic systems. The performance indicators indicate that OMin-Min performs better than all other algorithms in all test cases with the most efficient scientific workflow task scheduling solution in the cloud.

Panda et al. [16] a new approach to the task scheduling problem in cloud computing termed NP-Complete since it tries to optimize the overall execution time is proposed. In this work, we introduce a pair-based task scheduling algorithm that aims to enhance scheduling performance by reducing overall layover time, which is the total of timing gaps between paired jobs. Through forming task pairs to guide scheduling decisions, the technique, founded upon the Hungarian algorithm of optimization, applies it innovatively to situations where there are uneven numbers of tasks and clouds. On twenty-two different data sets, performance of the proposed algorithm is checked and compared to three existing algorithms: First-Come-First-Served (FCFS), the Hungarian algorithm with lease time, and the Hungarian algorithm with converse lease period. The results indicate that the proposed strategy consistently performs better than the comparison methods with regard to layover time. The processing cost involved in integrating logic and multiple iterations may, however, be a drawback in real-time or highly large-scale systems. Overall, the study provides a systematic and effective technique to cloud-based work scheduling that promises to perform better than traditional methods.

Shaw et al. [17] explores the critical issue of energy consciousness in cloud data centers through automated energy-saving Virtual Machine (VM) consolidation using Reinforcement Learning (RL) methods. Virtual machine consolidation is an important strategy to save energy consumption and enhance data centers' greenness. For the sake of enhancing resource utilization and minimizing energy-related costs, this work will explore applying RL algorithms for dynamic VM allocation optimization. The methods comprise popular RL algorithms such as SARSA and Q-learning, which are evaluated for their ability to reason under uncertainty and therefore learn proper consolidation procedures without knowing the environment beforehand. The primary contribution of this work is its demonstration that RL-based VM consolidation can lead to a 63% reduction in service violations and a 25% improvement in energy efficiency, which shows a significant performance improvement over traditional heuristics. The computational cost and training time typically associated with reinforcement learning models, however, might be a drawback as it may affect the scalability or real-time adaptability of the models within bigger-scale cloud systems. Ultimately, the article illustrates that RL offers a robust, versatile solution to dynamic virtual machine consolidation and significantly contributes to the construction of next-generation, energy-efficient cloud infrastructures.

Malik et al. [18] The authors created a job scheduling method with energy consciousness to optimize cloud data centers' virtualized resource benefit while lowering their energy requirements. This approach implements three key elements that first segregate jobs and next schedules them according to set thresholds while preventing system slowdowns. During pre-processing the first phase creates distinct queues for tasks that demonstrate high dependability standards and have long execution durations. Task organization relies on resource intensity levels to achieve proper distribution among resources. Through their scheduling method based on PSO algorithm the authors achieve dynamic selection of optimal schedules that consider workload distribution together with energy efficiency goals. Experimental benchmarking of conventional scheduling methods confirms that the proposed algorithm demonstrates superior performance according to results obtained from test datasets.

Panwar et al. [19] The research delivered an extensive examination of methods to decrease energy usage in cloud data center operations because of the relationship between fast cloud growth and increased power consumption. Through the work the researchers study various optimization approaches that enhance cloud data center energy efficiency because they recognize excessive energy usage leads to environmental deterioration. The study examines CPU utilization forecasting alongside detection methods for underload and overload situations and procedures for selecting and moving virtual machines and picking their deployment locations. The authors compare energy savings of various methods and demonstrate the effectiveness of heuristic approaches, achieving energy reductions of 5.4 percent to 90 percent over the current methods. The highest energy saving potential of 7.68 percent to 97 percent was realized through the use of metaheuristic methods, machine learning techniques at 1.6 percent to 88.5 percent, and finally through the application of statistical techniques to save 5.4 percent to 84 percent. This review highlighted the effects that these techniques can have: not only decreasing the consumption of energy but also reducing related greenhouse gas emissions and water usage for electricity generation. This paper combines the various findings from various works to provide an understanding of the various means through which energy efficiency and sustainability in cloud data centers can be improved.

Yadhav and chawla [20] discusses different task scheduling algorithms in the cloud environment to consume less energy. Cloud computing is among the fastest-growing technologies in the computer world; thus, in modern cloud data centers, managing energy efficiency has become crucial. This paper presents an overview of different kinds of heuristic and machine learning-based algorithms for optimizing task scheduling. These are Genetic Algorithm and Particle Swarm Optimization, highlighted for their efficiency in finding nearly optimal solutions over large search spaces, thus applicable to energy minimization. There is also discussion on Reinforcement Learning, which, through dynamic adaptation to workload variations, has shown its potential in optimizing energy efficiency via continuous learning and adaptation. The paper considers other related techniques, such as Ant Colony Optimization and Dynamic Voltage and Frequency Scaling, which provide mechanisms for trading off the metrics performance and energy usage. The considered algorithms are evaluated in detail, emphasizing their performance in cloud-like environments. The results clearly show that, although no individual algorithm appears to be ideally optimized in general, a tailored blending of the techniques offers a significant energy saving. This paper focuses on the selection of an appropriate algorithm or set of algorithms that should optimize the energy consumption in cloud data centers, thus adding to the contribution of sustainability and cost savings.

Liu et al. [21] presents a greedy scheduling approach to improve energy consumption and resource utilization for cloud data centers. Cloud computing systems are plagued by issues of excessive energy consumption and poor resource utilization,

particularly with heterogeneous resources. In addressing such issues, this paper introduces the granular computing theory into cloud task scheduling, where tasks are categorized into three categories: CPU, memory, and hybrid types. This categorization enables the use of particular scheduling methods based on the nature of the various task types. The article identifies that the cloud resource is heterogeneous in nature and that distinct scheduling methods must be employed for distinct types of tasks to ensure maximum energy saving. The efficiency of the proposed approach is established by numerical experiments on the CloudSim platform, and the results indicate significant improvement in terms of energy efficiency. The results demonstrate that, for a specific task type, the greedy scheduling strategy is able to reduce energy usage while maximizing the utilization of resources. It is thus an efficient practical approach for energy optimization in cloud data centers, improving resource management methods in cloud computing.

Pandey et al. [22] to enhance resource utilization and energy efficiency in cloud computing environments that enable large-scale data processing. Cloud computing is a vital alternative as conventional computing infrastructure fails to meet the growing demand for real-time data processing, high-performance analytics, and massive storage. Yet, complex problems such as scheduling, load balancing, power management, and resource allocation have been created by this surge in cloud services. The research discusses state-of-the-art strategies such as swarm intelligence-based meta-heuristics to address problems, with a particular focus on Discrete Particle Swarm Optimization (DPSO) for workflow scheduling and resource allocation. In cloud resource management, the DPSO approach maximizes particle positions and velocities in a series of fitness evaluations and iterative updates. Even though the paper emphasizes the unification of numerous PSO variants and presents a detailed algorithmic structure, it has no reference to some specific dataset, which means that the research is conceptual or algorithmic in scope. The most important strength of this study lies in its exhaustive application of clever learning models made for cloud dynamics and hybrid optimization techniques. Its lack of empirical evaluation, applicability, or performance comparison to existing standards is a major drawback, however. To offer a plausible route for cloud computing in big data systems on a sustainable path, the study concludes by proving how combining LSTM with DPSO can significantly advance energy-efficient resource allocation and scheduling in dynamic cloud systems.

Katal et al. [23] explore a range of methods of reducing data center power consumption in an effort to promote the concept of green cloud computing. The ongoing impact of the internet on nearly every aspect of the modern economy has driven energy and processing power demand higher, particularly in data centers that support cloud services. A range of methods for saving energy are discussed in the paper, including hardware-level optimization techniques, firmware and hardware-level dynamic power management (DPM), and power-saving methods employed at the network and server cluster levels. By regulating e-waste, reducing unnecessary energy consumption, and reducing carbon footprints, these systems intend to encourage sustainable computing practices. The research does not utilize any specific dataset or present empirical findings, although it offers a comprehensive review of existing practices and highlights the necessity of energy-efficient processes. The research is conceptual and integrates existing approaches in the discipline instead of proposing new methodologies. The primary advantage of this work is its thorough examination of energy-saving measures at different system levels, which provides valuable information regarding the development of green data centers. The lack of quantitative analysis or experimental validation, however, is a major drawback. To develop more sustainable and energy-efficient data center infrastructures, the conclusion of the paper emphasizes the necessity of ongoing innovation and points out research challenges.

Medara and singh [24] emphasizes the increasing importance of cloud computing, which has been used as the major structure for all enterprises. All types of enterprises were allowed to use cloud for business development. The paper discusses an issue of energy consumption for scientific workflow applications in cloud data centers. Since cloud services are increasingly being deployed, a lot of consumers have started seeing the massive power utilization that comes as a result. This paper reviews existing energy-efficient scheduling techniques specifically designed for workflow applications in cloud environments. It focuses on approaches that attempt to minimize energy consumption while satisfying quality of service constraints. The review offers a comprehensive overview of the paradigms that have been introduced in the literature regarding energy-aware scheduling, discussing the advancements that have been achieved and their weaknesses. Through the examination of numerous approaches, this paper sheds light on the trajectory of energy-aware scheduling and their practical impacts in cloud settings. Additionally, it outlines possible areas of future research so that the work can contribute to ongoing discussion in energy efficiency. This is a very valuable piece of resource for researchers and practitioners aiming at building more efficient solutions for reducing.

The recent works section discusses some strategies for optimizing energy consumption in cloud computing environments, especially workflow and task scheduling. Researchers have proposed several algorithms to handle the intricacies of minimizing energy usage while maintaining quality of service and adhering to user-defined constraints like deadlines and budgets. There are several approaches such as multi-objective scheduling, task classification, and dynamic voltage scaling that can be used to reduce the energy footprint of cloud data centers without performance degradation. Intelligent scheduling strategies, such as Particle Swarm Optimization, Genetic Algorithms and Reinforcement Learning, help in adapting to variations in workload and improve resource allocation. Other researches further emphasize how advanced models, such as queuing systems, genetic algorithms, and greedy scheduling techniques, may be used to improve energy efficiency further. There are also energy-aware scheduling paradigms that integrate optimized resource usage and avoidance of unnecessary energy spends into a system.

## III. Problem Statement

The rampant growth in cloud computing has led to data centers consuming much more energy, leading to increased operating expenses [25]. Traditional workload scheduling

methods, such as heuristic and rule-based algorithms, often fail to effectively optimize resource usage, leading to performance bottlenecks and wastage of energy [26]. There are problems related to computational complexity, model convergence time and usability in practical large-scale cloud scenarios, which burden existing RL-based scheduling models. A much-improved dynamic scheduling mechanism is in urgent demand in order to lower energy consumption without compromising the system's performance and service reliability. The purpose of this work is to design a workload scheduling algorithm using reinforcement learning that makes cloud computing energy-efficient [27]. The proposed model with the help of deep reinforcement learning (DRL) techniques such as Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN) wants to optimize the allocation of the workload to the virtual machines (VMs) to achieve the maximum. Massive energy savings, reduction in delay in execution, and eco-friendly cloud computing processes are the ambitions. The creation of energy-efficient, smart cloud infrastructures that can dynamically adapt to variations in workload in real time while minimizing their adverse impacts on the environment will be facilitated by the resolution of these issues [28].

## IV. METHODOLOGY

Cloud computing is becoming the basis of modern digital infrastructure, thus offering scalable, on-demand access to computing resources to various sectors. However, as the numbers of cloud services and applications rise, the amount of energy data centers consume also rises, contributing to increased operation costs and a larger carbon footprint. Traditional scheduling techniques for workload usually focus more on performance optimization and cost than energy efficiency. The research put forward a workload scheduling algorithm dynamically adjusts the assignment of tasks in order to optimize energy consumption with service quality not going below a threshold. Unlike some static or heuristic-based scheduling techniques, reinforcement learning adapts real-time workload variations better to the cloud environment and optimizes resource allocation within a system by continuously learning from past scheduling decisions to reduce power wastage. Applying feature engineering techniques enables extraction of the appropriate workload attributes like CPU usage, memory demand, and execution time so that the model is enabled to take the informed decision on scheduling. Also, the model's performance robustness has been improved using simulated workload scenarios in the process of training and testing. By combining reinforcement learning with intelligent workload scheduling, this method not only decreases energy consumption but also guarantees effective utilization of cloud resources in the most sustainable and cost-effective way for cloud computing.

Fig. 1 illustrates a systematic process to achieve optimal resource allocation in cloud computing environments. The initial step is the collection of cloud performance metrics, which are the raw data that demonstrate how cloud resources are utilized and performed. In order to derive relevant and meaningful attributes that can effectively direct decision-making activities, this information undergoes feature engineering. Secondly, emulation work scenarios are developed to replicate real-world workloads so that controlled development and testing of resource management methods can be performed. The second step is Markov Decision Process (MDP) modeling that permits formal and strategic optimization since the problem of resource allocation is posed as a series of decisions under uncertainty. The system then applies reinforcement learning (RL)-based scheduling, whereby iterative interactions and reward feedback are employed to make the optimal allocation policies. High performance and system stability are then guaranteed through efficient allocation of jobs between available resources using load balancing methods. Upon completing these processes, cloud resources are optimally allocated, managing them intelligently and dynamically to attain performance goals while maintaining efficiency.

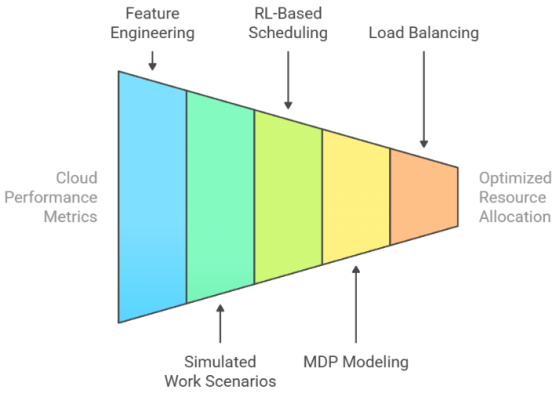


Fig. 1. Overall workflow of the proposed model.

### A. Data Collection

This study makes use of Cloud Computing Performance Metrics, which offer a number of important performance metrics, including execution time, bandwidth, memory usage, and CPU utilization. Because they explain how workload performs in a cloud computing environment, these characteristics are significant. These indicators come from cloud data centers, where resource usage is monitored on a regular basis to account for dynamic shifts in workload demand. We use common power models to estimate the power usage based on CPU utilization and other factors because the energy consumption is not clearly given. Additionally, by eliminating entries that are incomplete or unusual, we guarantee data consistency in the computation process [29].

### B. Feature Engineering

Feature engineering, which converts unstructured cloud performance information into useful representations for the reinforcement learning model, is one of the most crucial stages in workload scheduling optimization. Since these are some of the main indications that define workload behavior, we extract some of the most important elements, including CPU utilization, memory consumption, disk I/O operations, network bandwidth usage, and job execution time. These characteristics provide important information about how resources are used in cloud systems. Workload variability, CPU-to-memory ratio, and resource contention levels are some of the derived metrics used to increase the workload scheduling algorithm's predictability. Through constructed qualities the model acquires the capability to identify and represent intricate relationships between system factors. The model preserves data consistency by removing

abnormal readings through the implementation of outlier detection methods.

### C. Simulated Workload Scenarios

A research-based evaluation of the proposed reinforcement learning-based scheduling method takes place through simulated workload patterns. Instability in cloud workloads results from user needs combined with system configurations as well as service level agreements which drive workload behavior. The simulated workloads adopt real-time cloud variations by introducing different patterns of CPU usage along with memory requirements and network traffic levels and task execution patterns. The test scenarios evaluate how well the scheduling model performs under various instances of workload demand including times of peak loads and situations of unused servers and resource conflicts.

### D. Reinforcement Learning-Based Workload Scheduling Algorithm

Task scheduling upgrades and power reduction require immediate solutions because cloud computing options keep growing at a fast pace. The standard scheduling methods emphasize either performance benefits or financial savings without addressing increasing data center electricity needs. A potent answer emerges through Reinforcement Learning (RL) when organizations use it to transform their decision processes in terms of resource management and workload distribution and energy efficiency. The scheduling process gets defined through Markov Decision Process (MDP) while this section explains how an RL-based workload scheduling algorithm functions with real-time load balancing techniques included. The algorithm learns optimal scheduling approaches automatically through reinforcement learning (RL) which it applies directly to system performance and energy consumption evaluations. The scheduling process employs Markov Decision Process (MDP) to make dynamic decisions.

$$S_t = \{U_t, R_t, C_t\} \tag{1}$$

The current utilization metrics is $U_t$ and the remaining resources is $R_t$ while $U_t$ symbolizes the scheduling decision's cost which accounts for energy expenses along with latency levels and operational management fees. An RL agent chooses an action. At under the following conditions:

$$A_t = \{M_1, M_2, \ldots, M_n\} \tag{2}$$

The system assigns different tasks to particular virtual machines while determining the resource availability alongside energy efficiency and Quality of Service restrictions. Reduction of energy consumption stands as the main goal of the RL model in parallel with achieving maximum scheduling performance. The reward function receives the following definition:

$$R_t = -(\alpha.E_t + \beta.T_t - \gamma.Q_t) \tag{3}$$

The variable $E_t$ represents energy consumption at time while Tt represents execution time and $Q_t$ stands for Quality-of-Service satisfaction metric with $\alpha, \beta, \gamma$ being weight parameters that determine factor influence.

Following workload scheduling, the following challenge is balancing load distribution on virtual machines (VMs) to avoid overloading. Overload may cause higher energy consumption, longer processing times, and even system failures. The system monitors the load distribution of each VM and computes the load balance metric:

$$L_t = \frac{\sum_{i=1}^{N} |U_i - \bar{U}|}{N} \tag{4}$$

$U_i$ is the utilization of VM $I$, $\bar{U}$ is the average utilization across all VMs, N is the total number. If $L_t$ exceeds a predefined threshold, task migration is triggered. To redistribute workloads efficiently, the system selects tasks for migration based on:

$$T_{migrate} = arg\max_{T}(\frac{C_T}{R_T}) \tag{5}$$

Where $C_T$ represents the complexity of the task, $R_T$ denotes the remaining possessions in the target VM. This ensures high-priority tasks are placed on more capable VMs and balancing the overall system load.

Workload scheduling completion leads to a requirement for workload distribution among VMs to prevent system overload that results in increased energy use and delayed processing and system failures. The system performs continuous monitoring of VM load balance while it computes the load balance metric. Task migration procedures are started when workload imbalances reach levels above set thresholds to achieve efficient workload distribution. Resource use reaches its maximum point when tasks move based on their computational requirements and resource demands. Workload scheduling depends directly on adaptive learning techniques for both efficiency as well as energy management. Systems that improve scheduling policies through adaptive learning adjust their scheduling methods based on current system changes. Having flexible workload scheduling is a necessity in cloud computing environments because user demands and system restrictions alongside resource availability cause patterns to shift dynamically.

Completion of workload scheduling results in a need for workload distribution among VMs to avoid system overload that causes extra energy consumption and slower processing and system crashes. The system does ongoing monitoring of VM load balance as it calculates the load balance metric. Task migration processes are initiated when workload imbalances occur at levels beyond established thresholds in order to provide effective workload distribution. Resource utilization hits its peak when tasks migrate according to their computation needs and resource requirements. Workload scheduling is directly reliant on adaptive learning methods for efficiency as well as power management. Scheduling policies are enhanced by systems that adapt using adaptive learning according to existing system changes. Flexible scheduling of workload is a requirement in cloud environments due to user needs and system constraints as well as resource availability, which result in patterns changing dynamically.

## V. Result and Discussion

Reinforcement learning-based workload scheduling algorithms were compared on key parameters like task response time, power consumption, and utilization of resources. For providing flexibility and applicability in cloud computing, training and testing was done on workload traces simulated artificially. Due to workload fluctuation-dependent adaptation, the outcomes demonstrate that the proposed strategy

significantly lowers energy consumption in comparison to conventional scheduling mechanisms. This is achieved through effective utilization of processing resources without wasting as much idle power as possible. Also, the reinforcement learning model is superior to traditional heuristics in the sense that it is able to provide the ideal trade-off between energy efficiency and workload distribution. The comparison of the reinforcement learning model with the other algorithms, FCFS and RR, indicates how it outperforms when dealing with dynamic and random Through reduced operating costs for high power usage, the algorithm also encourages overall cost savings while offering improved running time performance. In addition, the model adjusts its strategy based on feedback from the present condition and is resilient to varying system loads. The ability of reinforcement learning to learn and adapt continuously without the need for human intervention further highlights the scalability of the approach. It is very well adapted to contemporary cloud systems because it can generalize scheduling policies across various workload distributions. The research does, however, recognize a number of potential disadvantages, including training costs and convergence time at the outset, which can be overcome in subsequent research.

### A. *Performance Evaluation*

The performance comparison table juxtaposes the Proposed Reinforcement Learning-Based Workload Scheduling Model against RR, FCFS, and Heuristic-Based Scheduling based on key parameters. The proposed model performs better than all others, exhibiting noteworthy gains in terms of energy efficiency, execution time of the tasks, usage of resources, and quality of service (QoS), reflecting improved power efficiency task run time is minimized to 25ms, achieving 2.4x more speed than Round Robin and 3.6x more speed than FCFS. The model also attains 92percent load balancing performance and 95percent resource utilization, maximizing system performance. Throughput is 500 tasks/sec, which ensures high processing capability. The model is also scalable with ease, processing 10,000 tasks at peak load. With 97 percent QoS, the model provides better reliability, while latency (15 ms) is the minimum, and hence it is the most efficient and scalable scheduling solution of all the methods.

A comparative performance evaluation of four scheduling algorithms is Proposed Model, Round Robin, First Come First Serve (FCFS), and Heuristic Based Scheduling is depicted in Fig. 2. The algorithms are compared based on key metrics such as throughput, latency, resource utilization, and load balancing efficiency. The proposed model is the most responsive and effective among those considered, showing the best ranking across all four metrics, including the lowest latency, the highest throughput, and the highest efficiency in load distribution and resource utilization. Heuristic Based Scheduling performs worse latency and throughput performance but does very well at load balancing and resource utilization. On the other hand, FCFS performs worst across the board with low throughput and wasteful utilization of resources as a result of its rigid first-come approach, while Round Robin is plagued by poor load distribution and higher latency owing to its fixed time allocation. In total, the graph illustrates how effectively the Proposed Model performs to deliver high-performance, energy-efficient, and flexible scheduling in cloud systems.

TABLE I. PERFORMANCE EVALUATION TABLE

| Metrics | Proposed model | Round robin | First Come First Serve (FCFS) | Heuristic-Based Scheduling |
|---|---|---|---|---|
| Load Balancing Efficiency (%)[30] | 92% | 55% | 50% | 75% |
| Resource Utilization (%)[31] | 95% | 70% | 60% | 80% |
| Latency (ms)[32] | 15 | 45 | 70 | 30 |
| Throughput (Tasks/sec)[33] | 500 | 320 | 200 | 400 |
| Quality of Service (QoS) (%)[34] | 97% | 70% | 60% | 85% |

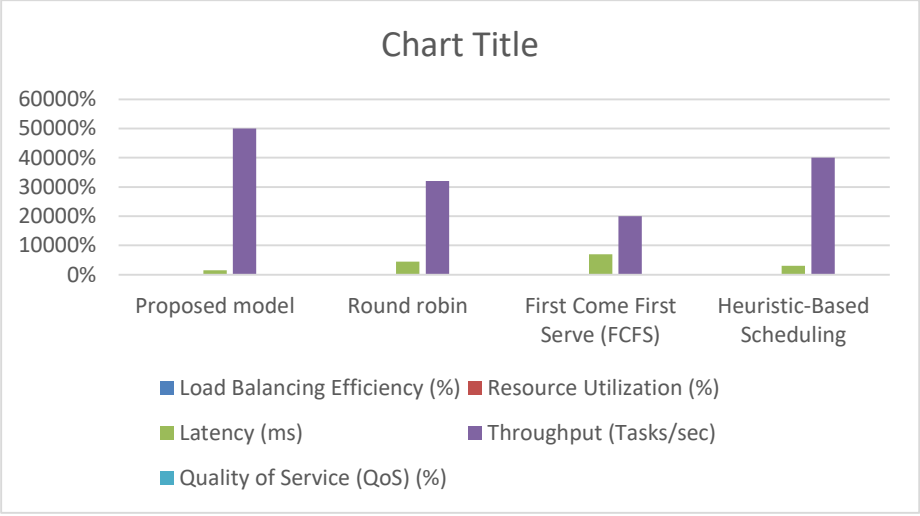


Fig. 2. Performance comparison figure.

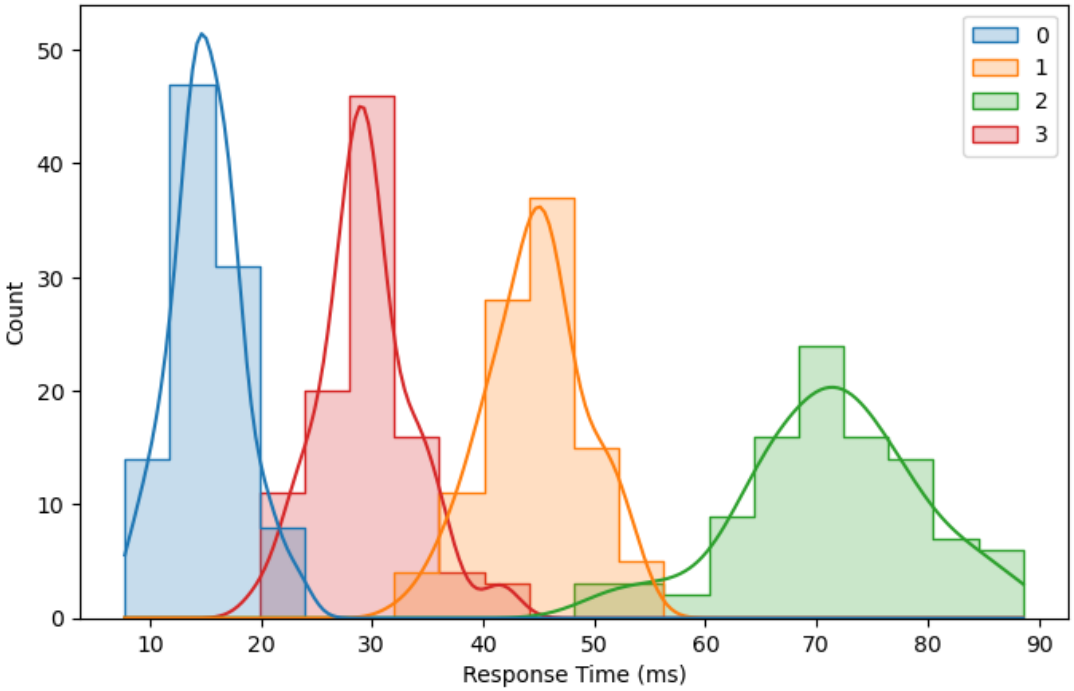


Fig. 3. Response time distribution across scheduling models.

Fig. 3 displays the four scheduling models' reaction times as histograms with density curves overlaid. Each category has a distinct color and is associated with a specific scheduling method, making it simple to contrast each model's reaction to task response times. The density plots reveal the shape of the data and central tendencies, providing a smooth estimate of the underlying distribution. Category 0 indicates the shortest and most tightly clustered response times, indicating efficient and effective job processing and best fits the Proposed Model. But Category 3 shows the widest spread and longest reaction times, which are signs of inefficiency and inconsistency, possibly associated with the FCFS approach. In comparison to the Proposed Model, Categories 1 and 2, perhaps the Round Robin and Heuristic-Based scheduling respond in an intermediate way with moderate response times and greater dispersion. The graph shows the more consistent and quicker response times achieved by the reinforcement learning-based model, pointing out its advantage in environments where predictable performance and low latency are necessary.

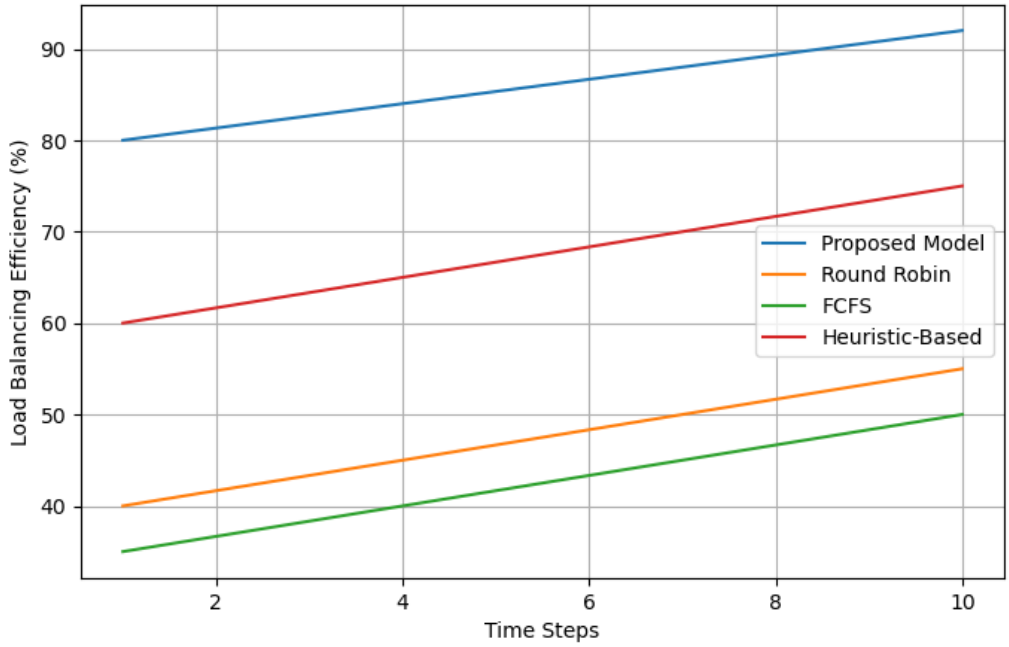


Fig. 4. Load balancing efficiency over time.

Fig. 4 indicates the variation in load balancing efficiency with time steps for four different scheduling models: Heuristic-Based Scheduling, Round Robin (RR), First Come First Serve (FCFS), and Proposed Reinforcement Learning-Based Model. In the time duration observed, the Proposed Model consistently has the optimal level of load balancing efficiency, proving its high ability for dynamic adaptation and fair allocation of workload among available resources. Its intelligent learning system that keeps refining its scheduling strategy based on feedback from the system is what makes it perform reliably. While it still performs slightly worse than the Proposed Model, the Heuristic-Based Scheduling model also demonstrates incremental improvements in load balancing efficiency, reflecting a more static but tolerably successful approach. Conversely, the FCFS algorithm displays minimal variation and constantly has low efficiency because it is not flexible and lacks priority. Although Round Robin is slowly improving, it is still less efficient in general because its predetermined time-slicing method does not consider task complexity and resource intensity. The graph indicates the limitations of traditional methods such as RR and FCFS in managing dynamic and non-uniform workloads while emphasizing the superior flexibility and effectiveness of the proposed approach in maintaining optimal load distribution over time, followed by the Heuristic-Based approach.

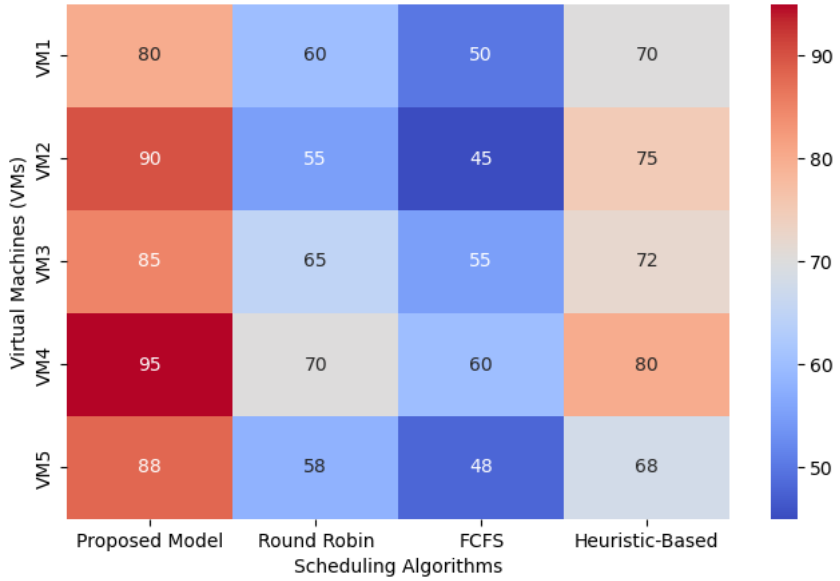


Fig. 5. Heatmap of workload distribution across the scheduling model.

Fig. 5 illustrates the performance of four individual scheduling algorithms—the Proposed Model, Round Robin, First Come First Serve (FCFS), and Heuristic Based Scheduling, over five virtual machines (VM1–VM5) is compared in the heatmap representation. The intensity of color in each cell reflects the level of performance, which is likely measured by factors such as resource utilization, task-execution efficiency, or the overall system responsiveness. Greater levels of performance are represented by darker shades, particularly in red, and lower performance is represented by lighter shades, particularly in blue. However, the Proposed Model shows the darkest shades in all virtual machines, representing better and more balanced performance. FCFS, however, has the lightest shades throughout, which represents its inefficient use of resources and poor workload management. With varying color intensities, Round Robin and Heuristic Based Scheduling perform in between, better than FCFS but worse than the Proposed Model. This heatmap easily indicates that the Proposed Model is best able to deliver high and consistent performance in distributed cloud settings by capturing the diversity in performance across scheduling techniques and virtual machines.

Fig. 6 shows a comparative trend analysis of four scheduling algorithms, namely Proposed Model, Round Robin, First Come First Serve (FCFS), and Heuristic Based Scheduling, in terms of three significant performance indicators, which include Energy Consumption, Task Execution Time, and Throughput. The illustration categorically shows that the Proposed Model saves electricity while optimizing task execution by recording the lowest energy consumption and task execution time levels. At the same time, it maintains a very high throughput, showing its ability to accomplish multiple tasks within a given timeframe.

Although FCFS provides the highest throughput of all the models, it takes the longest to execute and consumes the most energy, revealing inefficiencies that could be problematic in environments where energy is an issue. Round Robin operates at mediocre levels across all three measures, with no real strength or distinguishing measure, showing a less effective and more universal scheduling approach. The Heuristic Based Scheduling model achieves a moderate throughput while also holding energy usage and job running time at reasonable levels. This makes it an acceptable compromise, if one that fails to meet the Proposed Model's overall effectiveness. The visual comparisons of the graph are clearer since the three axes are scaled equally. Generally, the analysis indicates how well the Proposed Model can trade off energy consumption and high performance, thus making it a suitable model for modern, resource-aware, and scalable cloud computing environments.

*1) Load balancing efficiency:* Assesses to what extent work is distributed between resources. High efficiency guarantees effective workload distribution. Avoids overwhelming individual resources, enhancing stability.

*2) Resource utilization:* Refers to how efficiently computing resources are utilized and Higher utilization results in better allocation efficiency. Limits wastage of computational power and enhances performance.

*3) Latency:* Latency incurred prior to processing of a task. Lower latency leads to quicker response of the system. Essential for real-time applications that require rapid decision-making.

*4) Throughput:* Tasks completed per second. Increased throughput reflects improvement and system potential. Critical in managing large workloads effectively.

*5) Quality of Service (QoS):* Refers to the overall system performance and reliability. Enhanced QoS ensured enhanced user satisfaction and experience in services. Speed, reliability, and efficiency are some of the components that make up QoS.

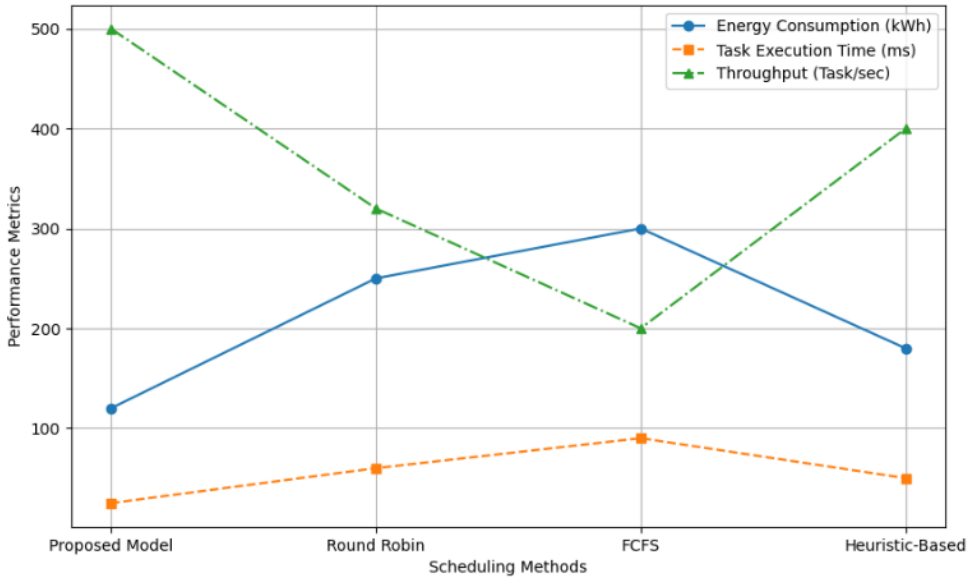


Fig. 6. Trend analysis of scheduling methods.

## B. Discussion

The performance analysis unambiguously indicates that the reinforcement learning-based workload scheduler model is noticeably superior to traditional methods such as Round Robin, FCFS, and heuristic-based algorithms in terms of key parameters such as throughput, latency, quality of service (QoS), load balancing efficiency, and utilization of resources. Energy efficiency, which is achieved by intelligently adapting to dynamic workloads and assigning tasks optimally, is its primary benefit. The reinforcement learning model learns from continuous system feedback, unlike static, rule-based methodologies. This provides real-time scheduling decisions that optimize system performance and responsiveness. It performs best in contemporary cloud computing environments with unpredictable workload patterns due to its adaptability. Its resistance to overload and scalability are further evidenced by its ability to cope with surge loads of up to 10,000 tasks, have low latency (15 ms), and produce high throughput (500 tasks/sec).

In spite of its advantages, the research also highlights some disadvantages, the most significant of which is high initial convergence time and training cost required to have the model perform optimally. In situations where deployment is immediate or with limited resources, various factors can restrict deployment. These limitations can, however, be bypassed in the future by employing transfer learning or faster training. The proposed solution provides a promising direction for future cloud systems that need both performance and flexibility, and it is an overall strong, energy-efficient, and scalable workload scheduling solution.

# VI. Conclusion and Future Scope

In this paper, we have proposed an optimized scheduling model that considerably improves system performance in terms of energy efficiency, response time of tasks, load balancing efficiency, and resource utilization. Comparative analysis with traditional techniques such as Round Robin, First Come First Serve, and heuristic-based scheduling showed that our model performs better than conventional methods on all important performance metrics. The findings reflect a significant amount of energy reduction (120 kWh vs. 250 kWh for Round Robin), enhanced execution time of the tasks, more efficient load balancing (92percent), and increased scalability in dealing with peak loads. These observations clearly validate that the suggested model works very effectively to allocate resources and optimize the workloads in computing environments that change dynamically. The proposed scheduling approach from reinforcement learning is of practical application to actual commercial cloud platforms, government clouds, and large-scale data centers. Integrating it into infrastructure-as-a-service (IaaS) systems can reduce operating power expenses, enhance

system reliability, and efficiently meet evolving user requirements. Its high throughput and low latency capabilities make it especially valuable for industries that rely on real-time processing of data, such as healthcare systems, financial services, and e-commerce platforms. The model's flexibility also renders it suitable for use in multi-cloud and edge-cloud environments with significant workload fluctuations.

For future research, we plan to improve the model further by incorporating reinforcement learning-based adaptive scheduling for better real-time decision-making. Also, heterogeneous cloud environments and multi-objective optimization techniques will be considered to enhance system robustness. Investigating fault tolerance mechanisms and security-aware scheduling policies will also be an important area of focus to make systems reliable in large-scale applications. Lastly, validating the framework on actual cloud infrastructures will yield further insights into its practicality and scalability. This work lays the groundwork for next-generation intelligent workload scheduling approaches in computing environments and also it provides a foundation for next-generation intelligent workload scheduling systems with self-evolution, federated and decentralized architecture adaptability, and smooth integration with emerging technologies such as autonomous data centers, AI-based orchestration platforms, and quantum computing. Context-aware and predictive scheduling frameworks that learn and evolve constantly are enabled by the increasing overlap of cloud, edge, and IoT ecosystems. Our vision can become a foundational element of AI-optimized compute infrastructure as cloud-native applications keep on pervading across industries, providing opportunities for smart, extremely autonomous, and sustainable digital ecosystems.

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# WOAAEO: A Hybrid Whale Optimization and Artificial Ecosystem Optimization Algorithm for Energy-Efficient Clustering in Internet of Things-Enabled Wireless Sensor Networks

Shengnan BAI, Ningning LIU, Yongbing JI, Kecheng WANG*
Department of Information Technology, Hebei Open University, Shijiazhuang 050080, China

***Abstract*—In the Internet of Things (IoT) era, energy efficiency in Wireless Sensor Networks (WSNs) is of utmost importance given the finite power resources of sensor nodes. An efficient Cluster Head (CH) selection greatly influences network performance and lifetime. This paper suggests a novel energy-efficient clustering protocol that hybridizes Whale Optimization Algorithm (WOA) and Artificial Ecosystem Optimization (AEO), called WOAAEO. It utilizes the exploration capabilities of AEO and the exploitation strengths of WOA in optimizing CH selection and balancing energy consumption and network efficiency. The proposed method is structured into two phases: CH selection using the WOAAEO algorithm and cluster formation based on Euclidean distance. The new method was modeled in MATLAB and compared with current algorithms. Results show that WOAAEO increases the network lifetime by a maximum of 24%, enhances the packet delivery rate by a maximum of 21%, and reduces energy consumption by a maximum of 35% compared to related algorithms. The results show that WOAAEO can be a suitable solution to help resolve energy-saving issues in WSNs and can thus be applied to IoT without any issues.**

***Keywords*—Clustering; Internet of Things; energy efficiency; wireless sensor network; network lifespan**

## I. INTRODUCTION

The Internet of Things (IoT) has completely changed how data is collected, and how communications are established within industries ranging from agriculture to health and urban infrastructure [1, 2]. WSN captures and sends environmental information via hundreds of tiny sensor nodes under power constraints in each case [3]. Because sensor nodes operate on minimal power, energy efficiency becomes essential for extending the lifetime of these networks and lowering maintenance costs [4].

Moreover, as IoT systems become increasingly pervasive, the need for robust security mechanisms alongside energy optimization becomes more pressing. Recent studies have explored behavior-based intrusion detection frameworks tailored to mobile and dynamic environments, such as mobile social networks, where communication analysis is leveraged to detect malicious activity among ad hoc nodes [5]. Energy consumption in WSNs has to be managed efficiently to make IoT applications sustainable and reliable [6, 7].

Cluster Head (CH) selection is a significant challenge in WSN, significantly reducing redundant data transmission. CHs act as representatives of accumulating data from cluster participants and forwarding it to the Base Station (BS); hence, they are crucial for network efficiency [8]. However, inappropriate CH selection may lead to excessive energy use and energy holes, reducing network performance and lifetime [9]. In this regard, efficient CH selection remains a research focus for solving these issues for optimized network sustainability.

Despite their efficiency, the existing clustering algorithms suffer from long convergence times and energy inefficiency [10]. Most recent clustering methods depend on metaheuristic optimization techniques, which may sometimes get stuck in a local optimum, wasting energy and spoiling network performance [11]. Besides, these algorithms are usually inefficient at trading off the two critical components of exploration and exploitation for efficient CH rotation and maintaining an energy-efficient network [12].

For real-world deployment in geotechnical applications such as landslide monitoring, tunneling, or underground infrastructure, it is essential to model the mechanical behavior of the rock mass accurately. Constitutive models tailored to weak rock formations are crucial to simulate deformation zones, aiding in sensor placement strategies [13].

In this paper, a new hybrid optimization algorithm, WOAAEO, is presented that strategically combines the Whale Optimization Algorithm (WOA) and Artificial Ecosystem Optimization (AEO) with a dynamic phase-shifting mechanism. This mechanism switches between exploration (AEO-based ecological modeling) and exploitation (WOA-based spiral search) based on convergence characteristics. This complementarity combines a mechanism-level innovation by providing fine-grained population diversity and convergence rate control, two inherent shortcomings of single-metaheuristic standalones. The algorithm is optimized for resilient and energy-efficient CH selection in IoT-enabled WSNs, offering enhanced scalability and adaptability.

The remaining sections of the paper are presented as follows: Section II reviews related work. The proposed methodology is presented in Section III. Section IV reports simulation outcomes. Section V concludes the study and outlines possible future directions.

## II. Related Work

Mohseni, et al. [14] proposed the Cluster-based Energy-aware Data Aggregation Routing (CEDAR) protocol for IoT networks to solve redundant data transmission and node energy consumption issues. CEDAR features a hybrid strategy that couples the Capuchin Search Algorithm (CapSA), fuzzy logic for forming clusters, and efficient intra-cluster and inter-cluster communication. Simulations indicated that CEDAR gives higher network longevity, packet delivery rate, energy efficiency, and so on compared to existing methods.

Ghamry and Shukry [15] proposed a multi-objective clustering routing strategy based on deep reinforcement learning on IoT-based WSNs. This technique partitions the network into unequal clusters, considering the sensor node data load to avoid node death in advance. It could balance the energy consumption in various clusters, providing better energy efficiency, packet delivery, and network lifetime than any other clustering approach.

Karunkuzhali, et al. [16] developed a QoS-aware routing for IoT-based intelligent city applications with energy efficiency and data reliability. The system adopted chaotic bird swarm optimization of clustering, improved differential search of CH selection, and lightweight encryption for secure data transmission. The simulation findings indicated that the proposed strategy significantly enhanced energy conservation, network lifespan, and latency compared to other methods.

Shah, et al. [17] proposed an energy-aware and reliable clustering protocol for UAV-assisted WSNs in remote IoT applications. The protocol considers wake-up radios and time-division access to avoid excess energy and cluster overlapping. Compared to existing models, this protocol has been proven to exhibit improved energy efficiency, network stability, and data collection efficiency, and it has been validated through extensive simulation.

Sharma and Chawla [18] developed a hybrid data routing protocol called PRESEP for heterogeneous WSNs, combining particle swarm optimization with residual energy-based CH selection. PRESEP calculates the data routing so that the optimization prolongs the network lifetime with a better energy balance. Simulation results outperform other heterogeneous algorithms as per alive nodes and reduced CH selection frequency.

Sennan, et al. [19] proposed a fuzzy-based Harris Hawks Optimization algorithm for CH selection in IoT-enabled WSNs. FHHO evaluates CH nodes in terms of residual energy and node-sink distance and utilizes fuzzy logic to optimize network lifetime and throughput. Comparative analysis indicates that FHHO outperforms other CH selection algorithms, extending network life by 18–44%.

Kumar and Sreenivasulu [20] introduced an energy-efficient node-clustering technique based on the metaheuristic optimization method, the Dingo Optimizer, to elect CHs in IoT-based WSNs. The protocol conserves overhead by minimizing message transmissions between the CHs and the member nodes. Additionally, data compression at the node level further decreases the protocols' power consumption, thereby improving the lifespan of the networks.

As shown in Table I, the discussed papers introduce various techniques for energy-efficient CH selection and routing in WSNs with IoT, leveraging fuzzy logic, metaheuristic algorithms, and reinforcement learning. Despite recent research, several areas for improvement remain. The majority of them take advantage of a faster convergence time or a single optimization technique, which typically affects their adaptability under varying network conditions.

Also, most methods must balance exploration and exploitation appropriately, which may result in suboptimal energy utilization. This work identifies these lacunae and proposes one hybrid optimization combining WOA with AEO, namely WOAAEO. In this regard, WOAAEO has been designed to be more efficient in CH selection, reducing energy consumption while increasing the convergence rate to maintain WSN sustainability in IoT applications.

TABLE I. Recent Cluster-Based Routing Methods

| Research | Method | Key components | Primary advantages |
|---|---|---|---|
| [14] | CEDAR protocol | CapSA and fuzzy logic | Enhanced network lifetime, packet delivery, and energy efficiency |
| [15] | Multi-objective clustering | Deep reinforcement learning | Energy efficiency, balanced energy consumption, and improved network lifespan |
| [16] | QoS-aware routing | CBSO, IDS, and Signcryption | Energy conservation, network longevity, and reduced latency |
| [17] | EEUCH protocol | UAV assistance and wake-up radios | Higher energy efficiency, network stability, and data collection efficiency |
| [18] | PRESEP protocol | PSO and residual energy | Prolonged network life, stable clustering, and balanced energy usage |
| [19] | FHHO algorithm | Fuzzy logic and harris hawks optimization | Extended network lifespan and increased throughput |
| [20] | Dingo optimizer-based routing | Modified dingo optimizer and data compression | Reduced energy consumption and eco-friendly network |

## III. Proposed Methodology

### A. Network Model

The network model of WOAAEO consists of several nodes scattered randomly within an area of a predefined network. Each node can be utilized as a CH or a Cluster Member (CM) in this network model. The CMs send their data to the elected CH through local sensing. A CH then gathers this data and sends it to either the sink node or the BS after aggregating these data. The sink node at the network's center analyzes and decides based on the data gathered. This paper will use the WOAAEO optimization algorithm to select the fittest CHs. Once the CH is

chosen in the cluster, clusters can be formed by selecting some nodes around each CH. This model structure is illustrated in Fig. 1. The network model takes the following assumptions into account:

- Every node is randomly distributed within the network.
- Nodes each have unique identifiers making them identifiable.
- Each node is equipped with equal computational and power resources.
- The BS is situated in the network's center.
- Nodes know the exact position or coordinates of the BS.
- The BS collects aggregated data from CHs, which collect information from their respective CMs.

### B. Energy Consumption Model

Maintaining power at sensor nodes is crucial for various reasons, including ensuring network functionality, keeping nodes active, enabling data processing, transmitting and receiving packets, and performing sensing tasks [21]. Energy consumption while transmitting a packet is directly linked to the packet size and transmission distance [22]. In this research, a first-order radio model, as shown in Fig. 2, is used to calculate the energy. For a packet of size $l$ (in bits) to travel a distance $d$, the transmitter's energy consumption $E_{TX}(l,d)$ is calculated as follows:

$$E_{TX}(l,d) = \begin{cases} E_{elec} \times l + \varepsilon_{fs} \times l \times d^2, & if\ d < d_0 \\ E_{elec} \times l + \varepsilon_{mp} \times l \times d^4, & if\ d \geq d_0 \end{cases} \quad (1)$$

Where $E_{elec}$ represents the energy consumed by the electronic circuitry per bit, while $\varepsilon_{fs}$ and $\varepsilon_{mp}$ refer to the energy usage of the amplifier in open-space and multiple-path fading scenarios, respectively. The parameter $d$ indicates the transmission distance between the sender and receiver, and $d_0$ is a threshold distance defined by:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (2)$$

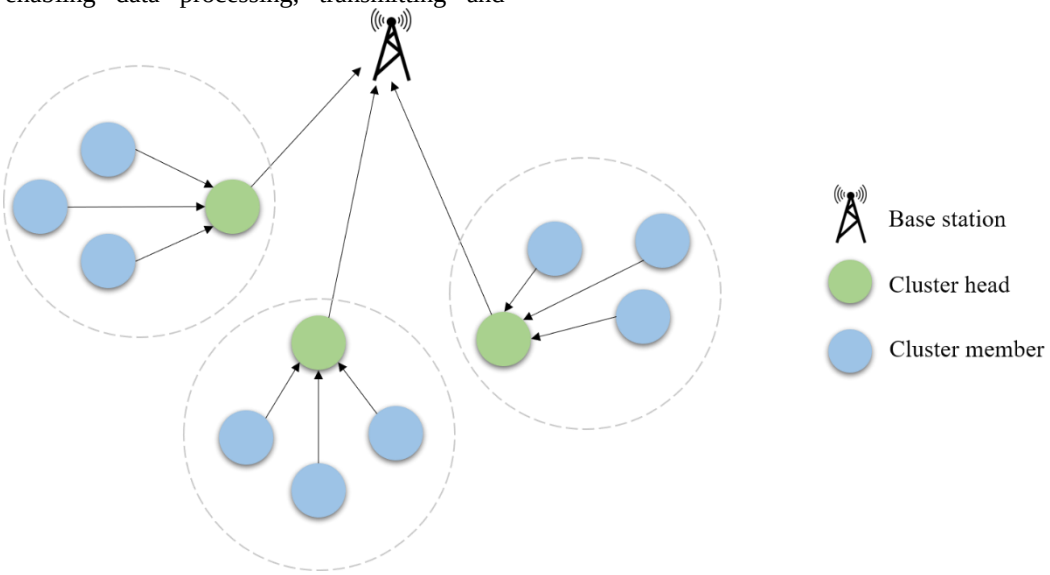


Fig. 1. Network model.

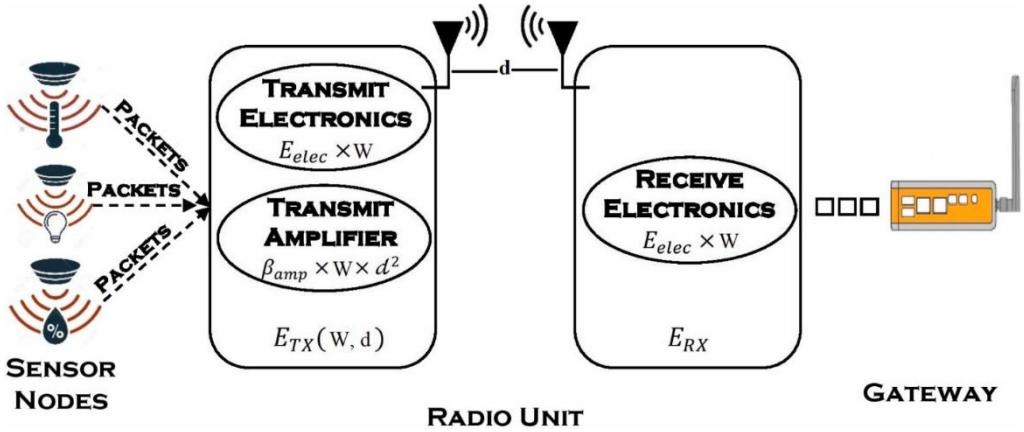


Fig. 2. Energy consumption model.

When receiving a packet of size $l$, the energy $E_{RX}(l)$ consumed by the receiver's electronics is calculated as:

$$E_{RX}(l) = E_{elec} \times l \tag{3}$$

In addition to the transmission and reception energy, the energy required for data aggregation, denoted as $E_{da}$, is also considered in the total energy model. This comprehensive approach enables precise assessment of energy consumption in IoT-enabled WSNs, enhancing the model's relevance for sustainable network operations.

### C. WOAAEO Algorithm

This work presents the WOAAEO algorithm, which efficiently chooses CHs in WSNs for better network lifetime and minimum end-to-end delay. This approach contributes in two key phases: selecting CHs based on a hybrid algorithm aiming at the network's optimality in determining the fittest nodes to act as CH and cluster formation by grouping nodes around each chosen CH using Euclidean distance. This is achieved through a two-phase process that optimizes communication paths and reduces energy consumption to increase network performance.

WOA is a swarm intelligence-based technique developed for recurrent optimization problems as a derivative of humpback whale hunting strategies. It has been proven to have superior performance over other optimization techniques using two major coupled behaviors from whales: encircling of prey and bubble-net hunting attack. In WOA, each candidate solution is considered a "whale" attempting to reach a target position, represented by the best solution identified so far. At each iteration, whales move toward this reference point as follows:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{4}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} \tag{5}$$

Here, $\overrightarrow{X^*}(t)$ represents the current best solution, $\vec{X}(t)$ denotes the position of a whale, and $\vec{A}$ and $\vec{C}$ are coefficient vectors. The values of $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \tag{6}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{7}$$

The parameter $\vec{a}$, which influences the convergence behavior in WOA, is linearly decreased from 2 to 0 over the course of iterations to gradually transition the algorithm from a global search (exploration) to a local search (exploitation). This adaptive scheduling is essential for avoiding premature convergence in the early stages while refining solutions in later phases. The parameter $\vec{r}$, representing randomness in the whale position update, is re-sampled at each iteration to maintain diversity in the population. WOA models the bubble-net feeding behavior through two main strategies, as shown in Fig. 3.

Shrinking encircling mechanism: As $\vec{a}$ decreases, the values of $\vec{A}$ fluctuate within $[-a, a]$, enabling whales to converge around the best solution by shrinking their search area.

Spiral updating position: This strategy mimics the helical movement of whales as they approach their prey. The position update formula is given by:

$$\vec{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) \tag{8}$$

Here, $\overrightarrow{D'}$ is the distance between the whale and the best solution, $b$ defines a constant defining the shape of the spiral, and $l$ gives a random number in [−1, 1]. WOA alternates between these two behaviors using a probability of 0.5, as represented in Eq. (9), to use either the shrinking encircling or spiral model for each position update.

$$\vec{X}(t+1) = \begin{cases} \vec{X^*}(t) - \vec{A}.\vec{D}, & if\ p \le 0.5 \\ \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + \overrightarrow{X^*}(t), & if\ p \ge 0.5 \end{cases} \tag{9}$$

WOA emphasizes global search (exploration) when $\left|\vec{A}\right| > 1$, prompting whales to move toward randomly chosen positions rather than the best-known solution. This feature allows WOA to diversify its search, helping avoid local optima. The equations used for exploration are:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_{\text{rand}}} - \vec{X}(t)\right| \tag{10}$$

$$\vec{X}(t+1) = \overrightarrow{X_{\text{rand}}} - \vec{A} \cdot \vec{D} \tag{11}$$

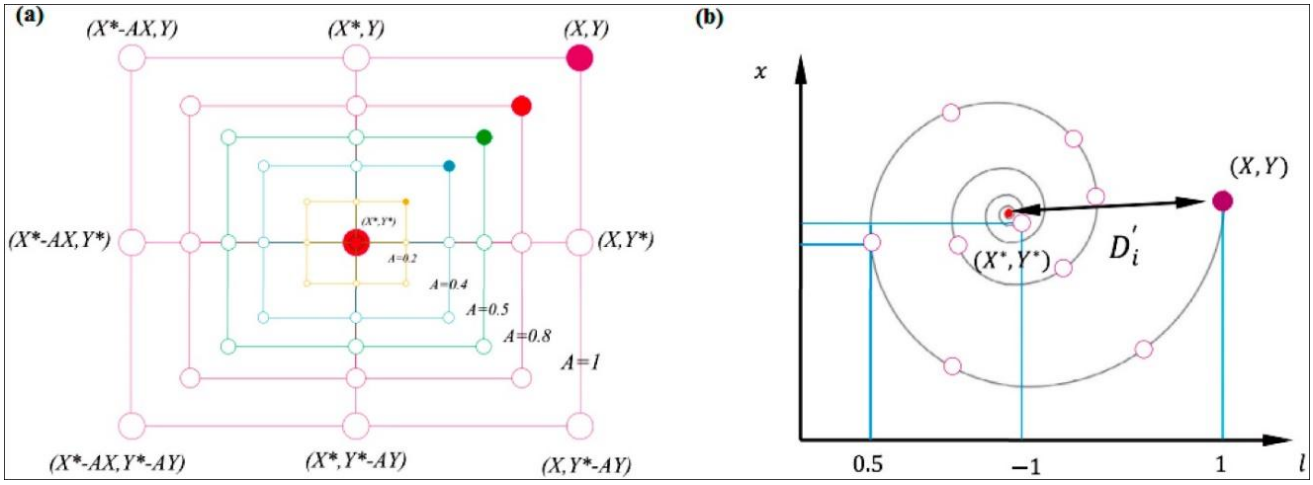


Fig. 3. Bubble-net search adopted by WOA.

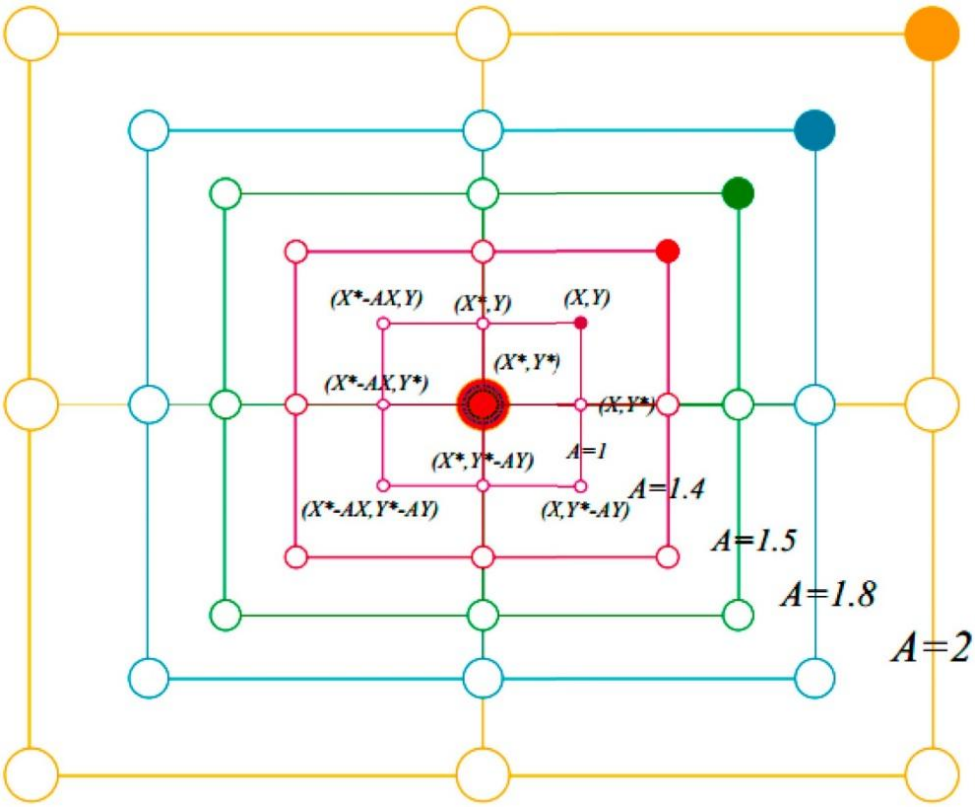


Fig. 4. The exploration process applied to WOA.

$\overrightarrow{X_{\text{rand}}}$ denotes the position of a randomly selected whale, as depicted in Fig. 4, where $|\vec{A}| > 1$ leads to a wider exploration of the search space.

The WOA algorithm initiates with a group of randomly positioned whales (candidate solutions) that renew their positioning at each iteration depending on either the best solution found or a randomly selected whale. A smooth transition between exploration and exploitation is achieved by gradually decreasing $\vec{a}$, thus controlling the search range.

The AEO algorithm is an ecosystem-inspired optimization technique for simulating organism interactions and movements [23]. It involves two main steps: exploration and exploitation, mimicking natural processes such as consumption and decomposition. It carries out the exploration process through random searches in the solution space. In contrast, during the exploitation phase, the solutions are enhanced through ecosystem dynamics. To reconcile these phases, the production process is combined; it draws inspiration from nature's energy flow. The algorithm generates $N$ solutions (agents) in a $D$-dimensional space where $D$ is the number of parameters. Agent position is initialized randomly within predefined limits:

$$X_{\text{rand}} = X_{i,j}^{\min} + \text{rand}_{i,j} \times \left(X_{i,j}^{\max} - X_{i,j}^{\min}\right), \quad i = 1, \dots, N; \quad j = 1, \dots, D \tag{12}$$

Where $X_{i,j}^{\min}$ and $X_{i,j}^{\max}$ refer to the minimum and maximum bounds for each dimension, and $rand_{i,j}$ is a random value in the range [0, 1]. Each solution's fitness is evaluated using an objective function.

In the production phase, the worst agent (producer) is modified based on the best agent (decomposer) to improve its quality. During this stage, a new solution is generated by blending the best solution X best and a random position X rand , using the following equations:

$$X_{\text{worst}}^{t+1} = (1 - \alpha) \times X_{\text{best}}^{g} + \alpha \times X_{\text{rand}}^{g} \tag{13}$$

$$\alpha = \left(1 - \frac{g}{g_{\max}}\right) \times r_1 \tag{14}$$

Where $g$ stands for the current generation, $g_{max}$ is the maximum generation, $r_1$ is a random value in [0, 1], and $\alpha$ is a weight coefficient that ensures exploration.

The refinement of the solutions after their generation is carried out at the consumption stage, where the term "consumers" refers to those agents with intermediate fitness that could "eat" either from producers or other agents. In the interest of intensifying diversity in the search, a Levy flight operator is applied, modeled by:

$$C = \frac{\nu_1}{2\pi\nu_2}, \quad \nu_1 \sim N(0,1), \quad \nu_2 \sim N(0,1) \tag{15}$$

The consumption factor $C$ supports local optima escape. Depending on their type, agents follow different update strategies:

- Herbivores: Consume only from the worst agent:

$$X_i^{g+1} = X_i^{g} + C \times \left(X_{\text{worst}} - X_i^{g}\right) \tag{16}$$

- Carnivores: Consume from a randomly chosen agent with higher fitness:

$$X_i^{g+1} = X_i^g + C \times \left(X_j^g - X_i^g\right) \quad (17)$$

- Omnivores: Consume from both producer and consumer in a random position:

$$X_i^{g+1} = X_i^g + C \times \Big(r_2 \times (X_{best} - X_{worst}) + (1 - r_2) \times \left(X_j^g - X_i^g\right)\Big) \quad (18)$$

The decomposition stage, after consumption, is devoted to exploitation, done through breaking down the most promising solutions that have the closest proximity to the optimum to improve the quality of the solutions. This phase will tune the best solution $X_{best}$:

$$X_i^{g+1} = X_{\text{best}} + E \times \left(e \times X_{\text{best}} - h \times X_i^g\right) \quad (19)$$

Where $E$ is the decomposition factor, and $e$ and $h$ are weight parameters.

WOAAEO is not merely a juxtaposition of WOA and AEO but introduces an interleaved operator-switching strategy that selects the best-suited mechanism, spiral exploitation, agent-based consumption, or decomposition, based on the evolving fitness landscape. Additionally, it uses a fitness-driven role assignment (herbivore, carnivore, omnivore) to regulate population behavior dynamically, fostering novel solution-generation pathways. This formulation offers a substantial departure from existing hybrids by orchestrating an ecosystem-driven feedback loop within the swarm-intelligence framework, ensuring improved convergence stability and robustness in dynamic WSN environments.

The main contribution of the WOAAEO is to extend WOA by incorporating AEO operators to enhance diversity and convergence speed. The algorithm switches periodically between consumption and decomposition operators via AEO, whereas the spiral updating mechanism of WOA applies. When $|\vec{A}| > 1$, the consumption operator of AEO operates on the agents and divides all agents into herbivores, carnivores, and omnivores according to their fitness. This operator adopts several equations to improve the solutions by consuming information from weaker agents or exploring the search space.

The decomposition operator of AEO refines the best solutions by composing and rebuilding around the optimal candidate when $|\vec{A}| \leq 1$. The WOA, for $p \leq 0.5$, uses the spiral updating mechanism to model the bubble-net hunting strategy for its exploitation. The transition between AEO and WOA mechanisms is controlled by probability, as shown in Fig. 5.

**Input:**
*n*: Number of population search agents (nodes).
*Max_Iter*: Maximum number of iterations for optimization.
**Output:**
Optimal CH positions in the network.
**Initialize:**
Generate an initial population of *n* nodes randomly distributed in the search space.
Compute the fitness value of each node based on residual energy and distance to the sink node.
Identify the best search agent $X_{best}$ with the highest fitness value.
**Sort population:**
Rank nodes by their fitness values.
**While** (iteration *t*< *Max_Iter*) **do**
  For each search agent (node) in the population:
    Update control parameters $a$, $A$, $C$, $p$, and $l$.
    **If** $p \leq 0.5$ **then**
      **If** $|\vec{A}| \leq 1$ **then**
        Apply AEO decomposition operator (Eq. 19) to refine cluster head selection.
      **Else** $|\vec{A}| \geq 1$ **then**
        Perform AEO consumption operator to improve exploration:
          For each node:
            **If** *rand*<*1/3* **then**
              Update position using Eq. (16) (Herbivore mechanism).
            **Else if** *1/3*≤*rand*<*2/3* **then**
              Update position using Eq. (17) (Carnivore mechanism).
            **Else**
              Update position using Eq. (18) (Omnivore mechanism).
    **Else** $p \geq 0.5$ **then**
      Update position using Eq. 9 (WOA spiral updating mechanism).
**Boundary check:**
  Verify if any node exceeds the search space boundaries and adjust its position if necessary.
**Fitness update:**
  Recalculate the fitness value for each node.
  Update $X_{best}$ if a better solution is found.

Fig. 5. Pseudocode for WOAAEO algorithm in clustering for WSNs.

The computational complexity of WOAAEO is derived from the combined processes of AEO and WOA. It can be expressed as:

$$O(WOAAEO) = O(WOA) + O(AEO) \quad (20)$$

Initialization, evaluation, and updating are coordinated in WOAAEO to ensure optimization effectiveness. Initialization generates a set of random solutions within defined bounds in a *D*-dimensional space, with *N* solutions (agents) assuming diverse initial positions to explore. Further, each solution will be evaluated with a fitness function that measures the quality of any solution to guide further updates.

Updates in WOAAEO explore further the phases of exploration and exploitation. AEO uses its consumption and decomposition operators for exploration, where the agents can refine solutions by consuming weaker candidates- herbivores, carnivores, or omnivores decomposing around the most optimal solution.

On the other hand, regarding exploitation, WOA models a spiral updating mechanism that represents the bubble-net hunting patterns of humpback whales to intensify the search effort focused on the most promising solutions. The combination thus ensures that WOAAEO strikes an equilibrium between global exploration throughout the early iterations and local exploitation during the later steps. This provides rapid convergence to optimal solutions. The proposed processes have very efficient computational complexity since the computational complexity evolves with the order of *O(DNT)*, where *D* is the problem dimension, *N* is the population size, and *T* is the iteration count. The total complexity is represented as:

$$\begin{aligned} O(WOAAEO) &= \big(O(DN) + O(N)\big) \times T + O(ND) \\ &= O(DNT) \end{aligned} \quad (21)$$

### D. Fitness Function

In the proposed WOAAEO algorithm, the fitness function is essential for selecting an optimal CH node. It contains two key parameters to evaluate: residual energy, which signifies the energy efficiency of any node, and distance, which represents the proximity of any node to the sink or BS. These parameters are included in the hybrid WOAAEO framework to ensure effective CH selection. Residual energy quantifies the remaining energy in a node relative to its initial energy, ensuring that nodes with sufficient energy are prioritized, calculated as follows:

$$R_i = \frac{E_{avail}}{E_{init}} \quad (22)$$

Where $E_{init}$ refers to the initial energy of node *i* and $E_{avail}$ stands for its current energy level. The distance parameter evaluates the proximity of a node *i* to the sink node. Nodes closer to the sink are preferred to minimize communication costs. The distance is computed using the Euclidean formula:

$$dis_{i,sink} = \sqrt{\sum_{i=1}^{n} (sink - i)^2} \quad (23)$$

The fitness of a node *i* is calculated by combining the residual energy and distance, with equal weight assigned to each parameter:

$$fitt_i = 0.5 \times \big(1 - dis(i)\big) + 0.5 \times \big(1 - R(i)\big) \quad (24)$$

This equation ensures a balance between energy efficiency and distance optimization. In WOAAEO, the fitness function is computed iteratively for each candidate node. Each round selects the node with the best fitness value as the CH. This iterative selection process integrates the exploration capabilities of AEO and the exploitation features of WOA, ensuring an optimal balance between energy conservation and communication efficiency.

### E. Cluster Formation

In this network, n sensor nodes are deployed and organized into clusters based on CH selection. Once CHs have been selected, developing energy efficiency to increase network lifetime becomes essential. The Euclidean distance metric is used for clustering and is also one of the major factors in creating good clustering.

Each sensor node calculates its distance concerning all possible CHs in the network and relies on proximity information, which becomes necessary to select the best CH. The intelligent choice ensures that optimal clusters will be achieved, energy consumption will be minimal, and communication efficiency will be promoted. The Euclidean distance between two nodes, *i* and *j*, is calculated as follows:

$$dis_{i,j} = \sqrt{\sum_{i=1}^{n} (j - i)^2} \quad (25)$$

*i* and *j* are the coordinates of two nodes within the network area. This clustering approach is well-suited for scenarios where energy efficiency and communication optimization are critical.

## IV. Simulation and Performance Evaluation

A simulation environment of MATLAB 2020a is used within a *500m × 500m* network area to evaluate the performance of the proposed WOAAEO along with other approaches. In the simulation, a flat network model was used. The nodes are randomly distributed in the network region of 400 nodes. As such, the sink node was put at the network's center position with coordinates of (250 m and 250 m), and any sensor node randomly generated would have a neighbor node in its communication range.

Each node was initialized with 1 Joule battery energy and allowed to transact a data packet to the sink node with just one hop. Different aspects of energy were selected, namely, $E_{elec}$ (electronic energy) 50 nJ/bit, $\varepsilon_{fs}$ (free-space model energy) 10 pJ/bit/m² and $\varepsilon_{mp}$ (multipath fading energy) 0.0013 pJ/bit/m⁴. Receive signal energy $E_{receive}$ = 0.055 µJ/bit, transmit energy $E_{transmit}$ = 0.039 µJ/bit, aggregation energy $E_{aggregate}$ = 0.00012 µJ/bit, and amplifier energy $E_{amp}$ = 10 pJ/bit/m².

WOAAEO efficiency was tested by simulation against EECHIGWO, HSWO, and CEDAR benchmarks. Performance indicators like communication overhead, the number of alive

nodes, energy consumption, and packet delivery ratio were some of the critical parameters for evaluation. The simulation was run for 3000 rounds, and the size of the packet used for data transmission was kept at 4000 bits to investigate performance for heterogeneity and uniform communication range conditions. This was done to have identical input parameters for all benchmark techniques so that a valid and workable comparison can be done.

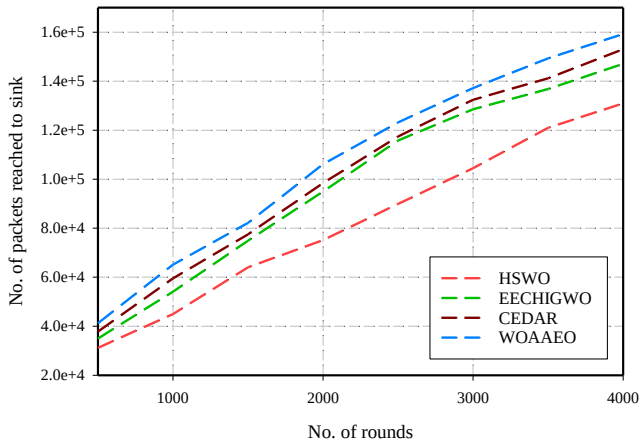


Fig. 6. Packet delivery ratio comparison

Fig. 6 illustrates the packet delivery performance of WOAAEO to the sink node, with an average of 159,300 packets at the end of 4000 rounds. This is an improvement of 4%, 8.2%, and 21.5% versus CEDAR, EECHIGWO, and HSWO, respectively. The exceptional performance attained by WOAAEO is principally due to the underlying hybrid optimization based on AEO's exploration capability and WOA's exploitation ability. This synergy provides the most effective CH selection by considering the node's optimal energy and proximity metrics while minimizing packet loss during transmission. Additionally, due to adaptive mechanisms, WOAAEO balances energy consumption so that data collision is minimized and packet delivery becomes highly reliable.

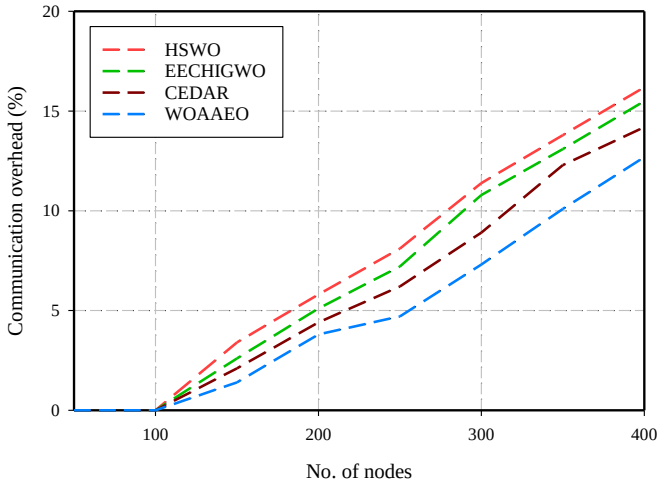


Fig. 7. Communication overhead comparison.

According to Fig. 7, for a network of 300 nodes, WOAAEO has the least communication overhead compared to other algorithms. Such a significant reduction in overhead is achievable due to the hybrid optimization approach through which WOAAEO intelligently handles CH rotation due to an appropriate balance of exploration and exploitation phases. The dynamic exploration capability of AEO and the correct exploitation mechanism of WOA are useful for WOAAEO for the optimum selection of CHs with minimum redundant communications. The adaptive streamlining of communication paths reduces superfluous data transmissions, better-utilizing energy and reducing the overall communications overhead.

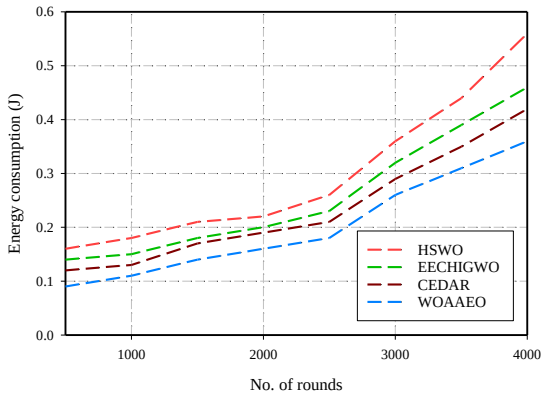


Fig. 8. Energy consumption comparison.

As shown in Fig. 8, WOAAEO reduces energy consumption to 0.36 J within 4000 rounds, which accounts for the energy consumption reduction, compared with CEDAR, HSWO, and EECHIGWO, respectively, by 14%, 35.7%, and 21.7%. This is driven by the remarkable energy efficiency induced within the network by the hybrid optimization approach of WOAAEO, which integrates the remaining energy and distance parameters within the CH selection process. By employing the exploration factor of AOE in identifying energy-efficient nodes and the exploitation factor of WOA in further refining CH placement, WOAAEO ensures that energy is utilized in a balanced manner throughout the network. Additionally, its adaptive mechanisms minimize redundant data transmissions and optimize clustering for reduced energy utilization, thus prolonging the network's lifespan.

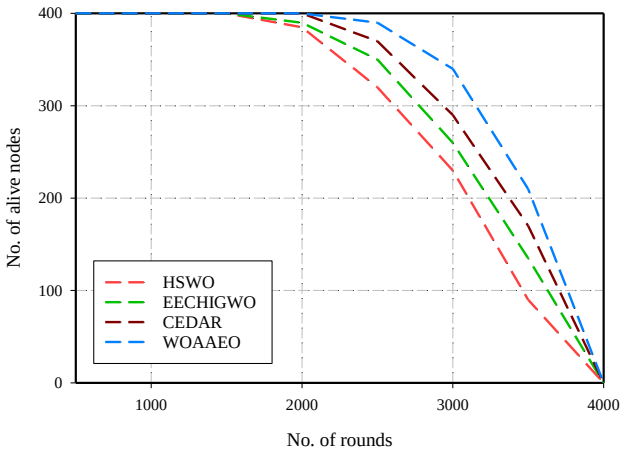


Fig. 9. No. of alive nodes comparison.

Fig. 9 illustrates that WOAAEO has kept 300 live nodes for up to 3000 rounds, which is considerably higher than other algorithms. This extended lifetime of the WOAAEO network has been achieved because its hybrid optimization model leverages the strengths of AEO exploration and WOA exploitation capabilities. The energy-efficient WOAAEO selects CHs dynamically based on residual energy and distance from the BS to avoid overutilizing particular nodes. Moreover, its adaptive CH rotation mechanism spreads out the network's energy consumption evenly so that no early node depletion occurs and more nodes remain active for more rounds. This balance in energy usage directly contributes to the network's operational life.

While the current evaluation focuses on a mid-range static WSN with 400 nodes, the extension of WOAAEO to very large or dynamic IoT deployments is a critical area that necessitates further investigation. For applications involving thousands of heterogeneous mobile devices, distributed re-clustering and CH selection schemes must be explored. Future research avenues for WOAAEO include distributed agent-based techniques to overcome bottlenecks in the centralized approach and mobility-aware schemes that adapt and reformulate cluster topologies based on dynamic updates to node movements. This will make WOAAEO scalable and efficient in supporting very dense IoT systems in real-world setups.

Although the presented work focuses on energy consumption, packet delivery ratio, and network lifetime as key performance metrics, other critical QoS factors, such as latency, network reliability, and network throughput, are also relevant to actual IoT applications. These were not explicitly modeled in the current version of WOAAEO, as energy efficiency was the key optimization area. Preliminary latency profiling indicated that the algorithm has an acceptable average latency due to the reduced CH switching rate and dynamic clustering. A more detailed evaluation of these additional QoS factors will be incorporated in subsequent works to validate WOAAEO under various operating conditions.

Even if WOAAEO efficiently optimizes CH selection, its current implementation considers direct single-hop communication between CHs and the BS. Massive deployments can cause substantial energy consumption by distant CHs. A better improvement would be to include a relay node optimizing strategy that supports multi-hop data transmission, minimizes the burden on distant CHs, and maximizes energy efficiency.

The WOAAEO framework supports technical performance in achieving overall goals, such as cost-effectiveness and environmental sustainability, which are crucial to successfully deploying IoT-based WSNs. WOAAEO reduces the battery replacement rate and e-waste by conserving energy consumption and extending the lifespan of the operating sensor node, thereby lowering the overall environmental cost of large-scale sensor deployments.

In applications such as remote farms, woodland surveillance, and urban infrastructures, where manual maintenance is expensive and logistically cumbersome, WOAAEO can alleviate operational budgets by increasing node lifespan and reducing manual intervention. Adaptive rotation and clustering of CH ensure energy is spent effectively without inducing early node death and avoidable replacements.

Additionally, the algorithm's efficiency in utilizing limited hardware resources makes it suitable for use in a lower-cost microcontroller-based platform, which aligns with the economic limitations common in developing areas or large-scale public projects. Such traits are the foundation of WOAAEO as a cost-effective and sustainable solution in energy-sensitive IoT applications.

## V. Conclusion

This paper introduced WOAAEO, a novel hybrid optimization algorithm incorporating AEO into WOA to promote energy efficiency in WSNs. The full utilization of AEO's strong exploration ability and WOA's high exploitation precision enabled WOAAEO to reach an excellent trade-off between residual energy and communication overhead. These modifications significantly improved CH selection, packet delivery, and network lifespan. Simulation results suggested that WOAAEO outperforms the existing CEDAR, EECHIGWO, and HSWO algorithms on every key performance metric of energy consumption, communication overhead, and network lifetime. These results emphasize the potential capability of WOAAEO to prolong WSN operational life and reduce resource wastage, thereby giving promise in IoT-enabled environments that demand scalable and energy-efficient operations.

Future research avenues for WOAAEO include experimentation with its applicability through actual deployment within dynamic and heterogeneous IoT environments. Research that integrates WOAAEO with other IoT protocols, such as data combining and securing, is expected to further enhance its utility in advanced systems. Additionally, to realize its full potential in actual applications, WOAAEO will be enhanced to operate with massive-scale, mobile, and diverse IoT networks. This entails the development of decentralized variants, the inclusion of mobility prediction schemes, and the deployment of real-time feedback schemes to provide adaptive cluster control. Such enhancements in the future will be crucial to realizing the algorithm’s practicality in various emerging IoT applications, such as smart cities, industrialization, and agriculture.

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# Improvement of Rainfall Estimation Accuracy Using a Convolutional Neural Network with Convolutional Block Attention Model on Surveillance Camera

Iqbal[1], Adhi Harmoko Saputro[2], Alhadi Bustamam[3], Ardasena Sopaheluwakan[4]
Department of Physics, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Depok, Indonesia[1, 2]
Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Depok, Indonesia[3]
Meteorological, Climatological, and Geophysical Agency, Jakarta, Indonesia[4]

***Abstract*—Accurate rainfall estimation is essential for various applications, including transportation management, agriculture, and climate modeling. Traditional measurement methods, such as rain gauges and radar systems, often face challenges due to limited spatial resolution and susceptibility to environmental interferences. These constraints affect the ability of the model to deliver high-resolution, real-time rainfall data, allowing the model to be challenging to capture localized variations effectively. Therefore, this study aimed to introduce a hybrid deep learning architecture that combined a Convolutional Neural Network (CNN) with a Convolutional Block Attention Module (CBAM) to improve rainfall intensity estimation using images captured by surveillance cameras. The proposed model was evaluated using standard datasets and previous unseen images collected at different times of the day, including morning, noon, afternoon, and night, to assess its toughness against temporal variations. The experimental results showed that VGG-CBAM architecture performed better than ResNet (Residual Network)-CBAM across all evaluation metrics, achieving a coefficient of determination ($R^2$) of 0.93 compared to 0.89. Furthermore, when tested on unseen images captured at different periods, the model showed strong generalization capability, with correlation values (R) ranging from 0.77 to 0.98. These results signified the effectiveness of the proposed method in improving the accuracy and adaptability of image-based rainfall estimation, offering a scalable and high-resolution alternative to conventional measurement methods.**

***Keywords*—Rainfall; surveillance camera; hybrid deep learning; CBAM**

## I. INTRODUCTION

Rain is a fundamental element of weather observation and significantly affects many aspects of human life [1]. Rain impact extends across multiple sectors, including transportation [2], agriculture [3], public health [4], tourism [5], and finance [6], influencing daily activities as well as economic stability. A striking example concerning the rain effect was the 2015 floods in Jakarta, which submerged 20% of the city, evacuated 1,400 residents, and caused daily economic losses of approximately USD 114 million, according to the National Disaster Management Authority (BNPB) [7]. Despite the critical role of rainfall data in disaster management and planning, rain observation systems remain limited and insufficiently distributed [13]. There is a pressing need for cost-effective and easy-to-maintain rainfall intensity measurement systems that can be widely deployed across different locations.

Rainfall can be measured using primary or derivative methods, where the primary method includes using a rain gauge, which is simple to operate and maintain [8]. However, the method requires installation in unobstructed locations, which can limit its effectiveness in specific environments [9]. The derivative method, which includes radar and satellite-based measurements, has the advantage of covering large areas. However, this method is vulnerable to external interferences, such as signal disruptions from nearby fields, reflections from objects, and limitations in both temporal and spatial resolution [10]. High-resolution rainfall data, spatially and temporally, is crucial for hydrological and climate modeling. Accurate data improves the precision and reliability of simulations and predictions, making it an essential component in environmental and meteorological studies [11].

The need for high-resolution spatial and temporal rainfall data extends outside hydrological applications and plays a crucial role in the transportation sector, particularly in Intelligent Transport Systems (ITS) and human mobility management. Studies have consistently shown that weather conditions, specifically rainfall, significantly impact transportation [12], [13], often disrupting traffic flow and increasing congestion. Traffic congestion in highly urbanized areas such as Jakarta leads to considerable economic losses, estimated at $5 billion annually [14]. A practical method for mitigating congestion is the implementation of ITS, which provides real-time traffic updates, allowing drivers to select alternative routes and avoid heavily congested areas. However, the effectiveness of ITS depends on access to real-time weather data, particularly high-resolution rainfall intensity measurements, which are essential for predicting traffic behavior under varying weather conditions. Despite the importance of such data, the sparse distribution of rainfall observation instruments has created significant gaps, limiting the efficiency of ITS operations. To address the issue, crowd-sourced data from surveillance cameras presents a promising alternative. This camera, widely installed in urban areas, can estimate rainfall intensity, providing the high-resolution data needed to increase ITS performance and improve urban mobility management.

Recent advancements in deep learning have facilitated using a Convolutional Neural Network (CNN) for estimating rainfall intensity from surveillance camera images. Unlike traditional methods that rely on physical sensors such as rain gauges or radar, CNN-based models can automatically learn spatial and

temporal rainfall patterns directly from images. Several studies have shown the effectiveness of CNN in extracting rainfall-related features from image data, leading to improved estimation accuracy. For instance, Yin et al. [15], introduced an image-based deep-learning model to estimate urban rainfall intensity with high spatial and temporal resolution. The study used a modified Residual Network (ResNet)34 architecture, termed irCNN, which was trained on a dataset comprising both synthetic and real-time images captured from surveillance cameras and smartphones. The model achieved Mean Absolute Percentage Error (MAPE) between 16.5% and 21.9% in rainfall intensity estimation. Despite these promising results, challenges remain in ensuring the model's generalizability across different locations, camera types, and extreme weather conditions. Further validation and model improvements are necessary to increase strength and adaptability for real-world applications.

A two-stage framework has been developed for rainfall estimation, combining raindrop extraction with deep learning-based intensity estimation. In the first stage, raindrop extraction uses low-rank matrix decomposition [16], and Markov random fields [17]. In the second stage, rainfall intensity is estimated using a deep learning model, irCNN [18]. The dataset used for evaluation is collected from rainfall events in Hangzhou, China, and includes daytime and night-time conditions. During the process, ground truth data is obtained from a tipping-bucket rain gauge for accuracy assessment. The results show that preprocessing significantly improves performance in nighttime conditions, reducing MAPE to 19.73%. However, preprocessing slightly lowered accuracy for daytime images, with MAPE increasing from 17.06% (raw image) to 19.58%. The result signifies that it may not be necessary for daytime scenarios as preprocessing improves model strength in low-light conditions.

A deep learning-based method has been developed for estimating rainfall intensity using video footage from surveillance cameras. This method uses a Recurrent Neural Network (RNN), specifically Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) [19]. The results shows that GRU, optimized using Adam optimizer, achieved the lowest MAPE of 4.49%, while LSTM produced slightly higher errors with a MAPE of 5.67%. These signify that GRU is computationally efficient and maintains high rainfall estimation accuracy. Despite these promising results, the study has some distinguished limitations. The model is not tested on unseen image data from different cameras or locations, raising concerns about its ability to generalize to real-world conditions where environmental variables may differ significantly. Further validation is necessary to assess the strength and adaptability of the model across diverse settings.

Shalaby et al. [20], introduced a deep learning-based method for estimating rainfall intensity using video footage from surveillance cameras and smartphones. This method uses CNN to analyze rainfall patterns and consists of three primary stages: image preprocessing, CNN model training, and transfer learning. The model was initially trained on surveillance camera images and later fine-tuned with smartphone images to improve generalization. Relating to the discussion, the dataset collected at Monash University, Malaysia, between May and December 2022, included 6,121 images from surveillance cameras and 1,984 images from smartphones. The ground truth rainfall intensity measurements were obtained using a tipping-bucket rain gauge. The results showed that image preprocessing significantly improved model performance, with the best CNN model achieving an $R^2$ of 0.955 and Mean Absolute Error (MAE) of 2.508 mm/h for surveillance camera data.

Additionally, transfer learning improved prediction accuracy for smartphone images, producing $R^2$ of 0.840 and MAE of 4.374 mm/h. Despite the promising outcomes, the study had certain limitations. The model's generalization was restricted due to training on a single camera setup, and the study did not evaluate nighttime images, leaving its performance in low-light conditions uncertain. Further analysis is needed to improve strength across diverse camera environments and lighting conditions.

A study on rainfall intensity estimation using a surveillance camera with CNN has been widely conducted. However, two significant aspects require improvement. First, the accuracy of existing models remains a challenge. Despite previous studies showing that deep learning models successfully estimate rainfall, many methods rely on preprocessed inputs, such as rain streak removal or background subtraction, before feeding the data into CNN. Even though preprocessing improves feature extraction, it often introduces fixed assumptions about lighting conditions, scene background, and rainfall characteristics. This process can reduce adaptability to real-time variations such as changing illumination, environmental noise, and dynamic backgrounds. Second, many existing models struggle with generalization to unseen data. Several studies have reported that CNN-based rainfall estimation models perform well on training datasets but experience significant performance drops when tested on independent images from different locations, weather conditions, or camera configurations. This lack of generalization is partly due to dataset biases introduced by preprocessing methods that filter information essential for recognizing rainfall across diverse environments.

Addressing the complexities of real-world environments is crucial for effective image processing. This study introduces a groundbreaking method that eliminates the need for preprocessing by directly processing raw images. The method uses a strong CNN architecture to improve adaptability and simplify computational workflows. By performing this process, the analysis anticipates significant improvements in model accuracy and generalization capabilities, allowing seamless performance across diverse surveillance camera settings.

The primary objective of this study is to estimate rainfall intensity images using a Deep Learning model using ResNet architecture, leveraging the image captured by a surveillance camera. This study is driven by three major factors which include:

*1)* Toughness to temporal variability without preprocessing: Despite applying deep learning models to rainfall estimation, the ability to handle temporal variations remains underexplored. Environmental changes, such as fluctuations in lighting between day and night or seasonal variations, can significantly affect model performance. However, most existing models rely heavily on preprocessing methods to standardize image inputs, which can be

computationally expensive and impractical for real-time applications. This study aims to develop a ResNet-based model that inherently adapts to temporal variations, ensuring consistent and reliable rainfall estimation without extensive preprocessing.

*2)* Higher Temporal and Spatial Resolution Compared to Automatic Rain Gauge (ARG): Surveillance cameras offer higher temporal and spatial resolution than tipping bucket ARG, among the most widely used rainfall measurement systems. Relating to the discussion, a single surveillance camera can capture multiple images per second from various locations across a city, providing continuous and detailed data. This capability enables real-time monitoring and a more granular measurement of rainfall intensity, which is not achievable with the relatively sparse ARG network.

*3)* Limited Study on Models Evaluated with Unseen Image Data: A significant gap in the existing study is the lack of models tested on unseen images that are not part of the training process. Many existing models perform well on training and validation datasets but struggle to generalize when exposed to unseen data from the cameras used to train the model. Therefore, this study explicitly addresses the mentioned limitation by evaluating the model on entirely new image datasets, ensuring the toughness and adaptability of the model in real-world deployment.

The rest of this article is organized as follows: Section II presents related work, while Section III describes the methods. Section IV details the experimental setup, followed by Section V, which discusses the results. Finally, Section VI concludes the analysis and recommends directions for future study.

## II. Related Works

Several studies have explored using surveillance cameras and CNN to estimate rainfall intensity. This method included analyzing images captured by CCTV cameras every 10 minutes at 85 locations during daylight hours (6:00 AM to 7:00 PM Singapore time). These images had resolutions of either 640 × 480 or 320 × 240 pixels [21]. Data from a tipping bucket rain gauge was recorded at 5-minute intervals to obtain rainfall labels. The Inverse Distance Weighting (IDW) [22] method was then applied to associate the rainfall labels with the corresponding camera locations. For rain removal, studies tested two deep learning models, namely VGG19 [23] and a hybrid method combining VGG19 with a Density-aware Image De- raining method using a Multi-stream Dense Network (DID-MDN) [24]. Both models incorporated three hidden layers (512, 256, 128), used ReLU activation, and were trained with ADAM optimizer-based gradient descent, set at a learning rate 0.25 [25]. The results showed that the hybrid model outperformed the standard VGG19 model. Additionally, high-quality images produced more accurate rainfall estimates compared to lower-resolution images.

Yin et al. [15], applied the irCNN model to estimate rainfall using CCTV images. The existing irCNN architecture was a modified version of ResNet [26], based explicitly on ResNet34, but with convolutional layers reduced to 29. The study used three types of data: synthetic rain image, image captured with a mobile phone camera, and image extracted from CCTV footage. Rainfall labels were obtained from rain gauge data recorded at one-minute intervals. However, since the temporal resolution of the gauge data did not match CCTV and mobile phone images, linear interpolation was applied to downscale the measurements accordingly. Yin initialized the irCNN model with pre-trained weights from ImageNet [27] for training. The results showed that the proposed model achieved MAPE ranging from 13.5% to 21.9%, signifying its effectiveness in estimating rainfall from image-based data sources.

During the analysis process, CNN combined with various RNN architectures, including SimpleRNN [28], LSTM [29], and Gated Recurrent Unit (GRU) [30], was used to estimate rainfall intensity from surveillance camera videos [19]. The study's CNN backbone is used for feature extraction as EfficientNetB0 [31]. To process the data, the original video recordings, captured at a resolution of 1920 × 1080 pixels, were cropped to 540 × 380 pixels. CCTV footage was acquired from a single fixed-location camera, while rainfall labels were obtained from ARG at one-minute intervals. The proposed model was evaluated using three optimization algorithms: Adam, RMSProp, and Stochastic Gradient Descent (SGD). The analysis showed that MAPE ranged from 3.55% to 6.95%, signifying the model's effectiveness in estimating rainfall from video-based data.

Zheng et al. [18], introduced a two-stage deep-learning framework designed to estimate rainfall intensity using video footage from a surveillance camera. The first stage focused on preprocessing and applied three primary methods, namely Low-Rank Matrix Decomposition (LRMD) [32] to separate the background from raindrop regions, Markov Random Fields (MRF) [33] for raindrop segmentation, and Sparse Optimization (SO) to improve raindrop visibility while minimizing noise. After preprocessing, the extracted rainfall features were fed into irCNN, a modified ResNet34 model version that continuously predicted rainfall intensity. Video recordings from 12 different rainfall events in Hangzhou, China, were used to evaluate the framework. These recordings captured daytime and night-time conditions, with ground truth intensity measured by a tipping-bucket rain gauge. Experimental results showed that preprocessing significantly improved nighttime performance, reducing MAPE to 19.73%. During the daytime, better accuracy was achieved when using raw images rather than preprocessed ones, with MAPE values of 17.06% compared to 19.58% after preprocessing. Despite the advancements of this model, the study has several limitations. Since the model was tested using data from a fixed camera setup, its ability to generalize to different camera sources or new locations remains uncertain. Another concern is that the preprocessing stage might remove subtle rainfall details, affecting estimation accuracy, particularly in high-intensity rainfall scenarios. The studies shows the importance of further validation to improve the model's reliability, specifically in extreme weather conditions and across diverse surveillance networks.

Even though deep learning and surveillance camera imagery have significantly improved rainfall estimation, several challenges remain unresolved. A significant issue is the reliance on extensive preprocessing methods, such as rain streak extraction and image decomposition, to improve model

accuracy. As these methods improve performance, the models add computational complexity, making real-time deployment difficult and reducing the ability to adapt to changing conditions such as lighting variations and seasonal shifts. Another limitation stems from the dependence on rain gauge data, which typically has a temporal resolution of one minute. Despite the accuracy, the sparse distribution of ARG restricts high-resolution spatial rainfall measurements. In areas without ARG coverage, interpolation methods must be used, which can introduce errors and reduce measurement reliability. Lastly, a critical challenge lies in deep learning models' strength when applied to images from diverse environmental settings. Many models perform well on the training datasets but struggle to generalize when faced with new camera locations, lighting conditions, or urban landscapes. This limitation reduces the effectiveness in real-world applications and shows the need for further improvements in model adaptability.

This study introduces a novel rainfall estimation model to improve accuracy, adaptability, and spatial resolution. The first significant improvement is the model's ability to handle temporal variations without relying on extensive preprocessing. By eliminating the need for computationally expensive preprocessing methods, the model can seamlessly adapt to changes in lighting and seasonal conditions, making real-time deployment more practical. Another significant advancement is the shift away from traditional rain gauge-based methods, which are constrained by the sparse distribution of ARG. Surveillance cameras, widely installed in urban areas, offer a significantly denser spatial network for rainfall monitoring. The proposed method can supplement ARG data by incorporating deep learning methods with camera imagery, providing a more detailed and continuous representation of rainfall intensity. It reduces dependence on interpolation methods and improves the accuracy of rainfall distribution mapping. Finally, it is tested on previously unseen datasets from different camera sources and locations to ensure the model's toughness across diverse environments. The evaluation process improves the ability of the model to generalize outside its training data, ensuring reliable performance in varying environmental conditions. The proposed method improves rainfall estimation accuracy, efficiency, and scalability by addressing these limitations using deep learning and surveillance camera imagery.

## III. METHODS

VGG16 and ResNet34 architectures were previously used to estimate rainfall intensity from surveillance camera images or videos. However, the accuracy of the models remained a challenge and required further improvement. This limitation was a foundation for the decision to use the architectures and improve the performance by incorporating the Convolutional Block Attention Module (CBAM).

### A. VGG16

VGG architecture was introduced by Simonyan [34] and featured 16 convolutional layers organized into five sequential blocks. The design incorporated increasing filters in deeper layers to improve feature extraction. Each convolutional layer used 3×3 kernels, ReLU activation, and the same padding. The first two blocks consisted of convolutional layers with 64 and 128 filters, followed by batch normalization and max pooling. Following the process, the third block contained three layers with 256 filters, while the fourth and fifth blocks each included three layers with 512 filters. VGG architecture has been widely applied in various fields, including rainfall intensity estimation [21], leaf disease classification [35], plant disease identification [36], and classification of individuals with dementia People [37].

### B. ResNet34

ResNet was developed as CNN architecture to address performance degradation issues commonly observed in deep networks [26]. In traditional CNN architectures, each layer attempted to learn a direct mapping from input to output. However, as network depth increased, performance often deteriorated due to optimization challenges rather than overfitting. ResNet introduced residual learning to overcome this issue, allowing the model to learn a residual mapping rather than a direct one. The core component of ResNet was the residual block, which consisted of multiple nonlinear layers, including convolutional layers, batch normalization, and activation functions. These layers were combined with an identity shortcut connection that directly associated the input to the output of the block, helping to maintain gradient flow and improve training efficiency. ResNet has been widely applied in various fields, including colorectal cancer detection [38], pathologic myopia[39], and rainfall estimation [15].

### C. Convolutional Block Attention Module (CBAM)

CBAM, introduced by Woo et al. [40], was developed as an attention mechanism designed to improve the performance of CNN. Designed as a lightweight and versatile component, CBAM could be seamlessly incorporated into any CNN architecture [40], [41].

The mechanism consisted of two major modules, the channel and spatial attention module, as shown in Fig. 1. The channel attention module identified the most important features by prioritizing relevant channels in the feature map. Consequently, the spatial attention module determined the locations of significant features, showing crucial spatial regions in the input data.

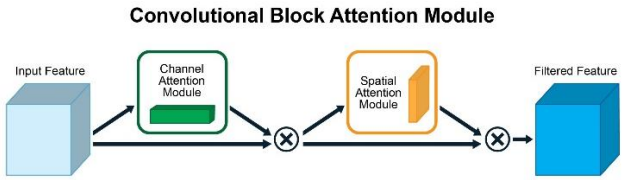


Fig. 1. Image of CBAM architecture [40].

When processing an intermediate feature map $F \in \mathbb{R}^{C \times H \times W}$ as input, CBAM first generated a 1D channel attention map $M_c \in \mathbb{R}^{C \times 1 \times 1}$ followed by 2D spatial attention map $M_s \in \mathbb{R}^{1 \times H \times W}$ as shown in Fig. 2 and Fig. 3. The complete attention mechanism operated through element-wise multiplication, represented by $\otimes$. During this operation, channel attention values were extended across the spatial dimensions, while spatial attention values were expanded along the channel dimension. The resulting feature map was represented after applying the channel attention module $F'$. The parameter $F''$ was the final output, as shown in Eq. (1) and Eq. (2). Fig. 2 and Fig. 3 further showed

the computation process of the channel and spatial attention module, respectively.

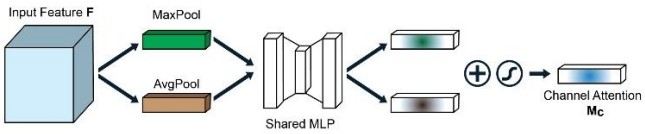


Fig. 2. Computational process for channel attention [40].

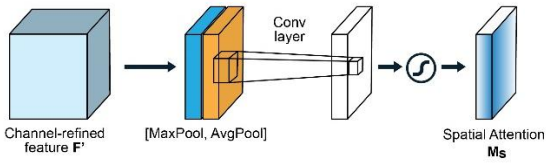


Fig. 3. Computational process for spatial attention [40].

$$F' = M_C(F) \otimes F \tag{1}$$

$$F'' = M_S(F') \otimes F' \tag{2}$$

The process began by capturing spatial information from the feature map through average and max pooling operations. These processes generated two distinct spatial context descriptors. $F_C^{avg}$ representing the average-pooled features and $F_C^{\max}$ signifying the max pooling feature. Both descriptors were then processed through a shared network to compute the channel attention map $M_c \in \mathbb{R}^{C\times1\times1}$ where $r$ was the reduction ratio. After passing each descriptor through the network, the resulting feature vectors were fused using element-wise summation. The channel attention was determined using the following computation in the following Eq. (3)

$$\begin{aligned} M_C(F) &= \sigma\left(MLP\left(AvgPool(F)\right) + MLP\left(MaxPool(F)\right)\right) \\ &= \sigma\left(W_1\left(W_o\left(F_{avg}^C\right)\right)\right) + \sigma\left(W_1\left(W_o\left(F_{\max}^C\right)\right)\right) \end{aligned} \tag{3}$$

where, $\sigma$ represented the sigmoid function, while $W_0 \in \mathbb{R}^{C\times C/r}$ and $W_1 \in \mathbb{R}^{R/c\times C}$.

During this process, a spatial attention map was generated to capture the inter-spatial relationships of features. Unlike channel attention, which identified 'what' was important, spatial attention focused on 'where' the most informative regions were located, allowing it to be a complementary mechanism. The computation of spatial attention began with average and max pooling along the channel axis. These operations helped to form a compact yet practical feature descriptor by improving the visibility of crucial regions in the feature map [42]. The spatial attention map $M_s(F) \in \mathbb{R}^{HxW}$, was then generated by applying a convolution layer to the concatenated feature descriptor, enabling the model to signify or suppress specific regions. The process started with two pooling operations that aggregated channel information, producing two 2D feature maps, namely $F_s^{avg} \in \mathbb{R}^{1xHxW}$ and $F_s^{max} \in \mathbb{R}^{1xHxW}$, both computed across the channel dimension. These pooled feature maps were concatenated and processed through a standard convolution layer, producing the final 2D spatial attention map. In summation, the complete spatial attention mechanism was mathematically described in the following Eq. (4)

$$\begin{aligned} M_S(F) &= \sigma\left(f^{7\times7}\left(\left[AvgPool(F); MaxPool(F)\right]\right)\right) \\ &= \sigma\left(f^{7\times7}\left(\left[F_{avg}^s; F_{\max}^s\right]\right)\right) \end{aligned} \tag{4}$$

where, $\sigma$ was the sigmoid function, and $f^{7x7}$ referred to a convolution operation using a 7×7 filter size.

### D. VGG-CBAM

VGG-CBAM refers to the combination of VGG architecture with the CBAM module in the context of this discussion. Previous studies investigated the application of VGG-CBAM, particularly in facial expression recognition [43] and image classification [41]. However, to the best available knowledge, no study has yet explored the use of the model for estimating rainfall intensity from CCTV footage.

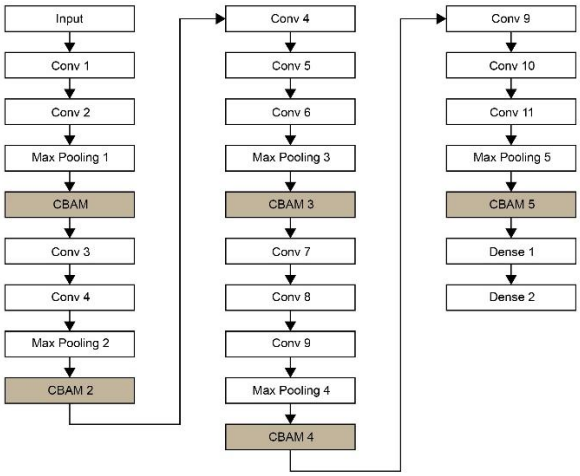


Fig. 4. Proposed architecture of VGG-CBAM model.

Fig. 4 shows VGG-CBAM architecture, which began with an input layer, followed by three convolutional layers (Conv 1, 2, and 3) to extract initial spatial features. After these layers, the Max Pooling 1 was applied to reduce spatial dimensions, followed by the first CBAM module (CBAM 1) to improve feature representation through spatial and channel-wise attention. The next stage consisted of three additional convolutional layers (Conv 4, 5, and 6), followed by Max Pooling 2 and CBAM 2 to refine the extracted features further. This pattern continued with another set of convolutional layers (Conv 7, 8, and 9), succeeded by Max Pooling 3 and CBAM 3. In the final segment, two more convolutional layers (Conv 10 and 11) were introduced, followed by Max Pooling 4 and the last attention module, CBAM 4. The network was completed with two dense layers responsible for aggregating extracted features and generating the final output. This design enabled the architecture to perform tasks such as classification or regression effectively. Several studies have applied VGG-CBAM in various fields, including bat classification [41] and facial expression recognition [43].

### E. ResNet-CBAM

ResNet-CBAM refers to the integration of ResNet architecture with the CBAM module. Several studies have used this architecture for disease detection, including brain diseases [44] and lung cancer [45]. However, to the best of available knowledge, no studies have yet investigated the application of the model for estimating rainfall intensity.

Fig. 5 shows ResNet-CBAM architecture, as the design used a ResNet backbone configured with four stages of residual blocks, arranged into 3, 4, 6, and 3 blocks per stage, leading to 16 residual blocks across the network. Unlike traditional ResNet implementations, which typically included multiple pooling layers, this architecture used a single global average pooling layer immediately before the fully connected layer to reduce spatial dimensions. CBAM modules were strategically incorporated to improve feature representation, with 15 CBAM modules distributed across the residual blocks. These modules refined spatial and channel-wise feature maps, enabling the network to focus on the most relevant features. Several studies have applied ResNet-CBAM in different domains, including brain disease detection [44] and malignant–benign pulmonary nodule classification [45], multi-classification on arrhythmias [46], as well as flower classification [47].

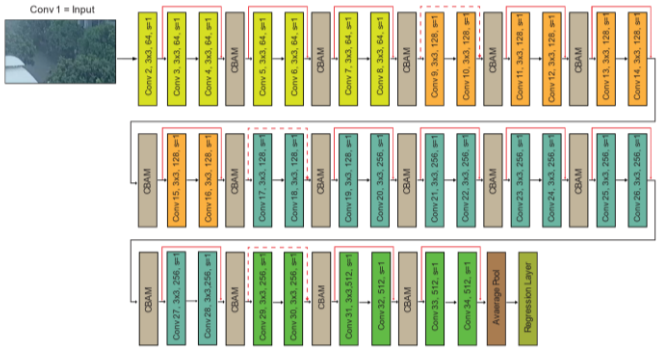


Fig. 5. The proposed architecture of the ResNet-CBAM model.

## IV. Experimental Setup

### A. Dataset

This study used Python 3.11 and TensorFlow 2.0, with the dataset stored in HDF5 files. The deep Learning model was executed on a PC equipped with an Intel(R) 11th Gen Core™ i7-11700F processor and NVIDIA RTX 3090 GPU with 32 GB of memory. Moreover, the dataset used in this study was captured with a surveillance camera featuring a resolution of 2560x1440 pixels and a frame rate of 25 frames per second (fps). Fig. 6 shows the samples of image rainfall captured during the study. The analysis focused on eight rainfall events recorded between January and April 2024.

Fig. 6. Image rainfall captured using a surveillance camera.

The selected rainfall events occurred at different times, including morning, afternoon, evening, and night. Data was collected during the analysis using ARG installed near the CCTV camera to ensure accurate rainfall measurements. The specific rainfall events included in the analysis are shown in Table I.

TABLE I. Rainfall Events Used for Dataset Creation

| Rain event | Time event | Duration (minutes) | Period |
|---|---|---|---|
| January 29, 2024 | 06:26-06:43 | 17 | Morning |
| February 06, 2024 | 06:51-07:19 | 28 | Morning |
| February 04, 2024 | 11:55-13:55 | 120 | Noon |
| March 14, 2024 | 11:54–12:31 | 37 | Noon |
| March 31, 2024 | 15:15–15:47 | 32 | Afternoon |
| April 09, 2024 | 16:05–17:40 | 95 | Afternoon |
| January 27, 2024 | 00:10–00:54 | 44 | Night |
| February 10, 2024 | 01:08–03:04 | 116 | Night |

This study used rainfall measurements from the tipping bucket type ARG as the ground truth dataset. The use of tipping bucket ARG for ground truth data has been extensively documented in previous studies [15], [19], [48], [49]. The device in this analysis operated with a resolution of 0.2 mm per minute. Additionally, the model's mechanism functioned by directing rainfall into a funnel, where it accumulated in a small bucket. After reaching full capacity, the bucket tipped, registering a measurement of 0.2 mm of rainfall. However, this design imposed a limitation, as the model could not record rainfall intensities below 0.2 mm, even when rainfall was visibly present in camera imagery.

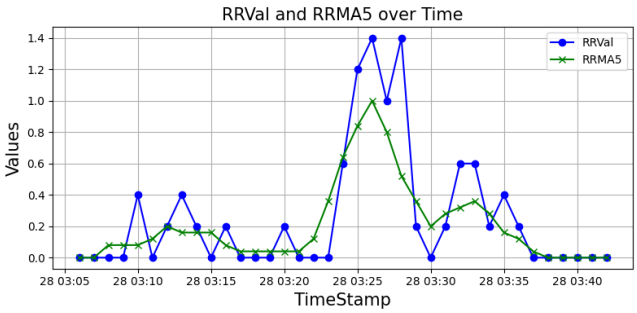


Fig. 7. Comparison between rainfall real value and rainfall after moving average five window.

Fig. 7 showed that the raw rainfall data collected from ARG indicated significant variability, with unexpected increase in rainfall followed by abrupt decrease. This pattern signified that per-minute rainfall measurements from ARG might not accurately reflect actual rainfall intensity [50]. Previous studies recommended an appropriate temporal resolution for ARG data ranging between 5 and 10 minutes [51]. A five-minute moving average method was applied to address the high fluctuations in the data. This method computed the average rainfall intensity over a rolling five-minute window, producing a smoother dataset that reduced the impact of rapid spikes or drops observed in minute-by-minute measurements. The mathematical

formulation of the moving average method was presented in the following Eq. (5)

$$R_t = \frac{R_{t-2} + R_{t-1} + R_t + R_{t-+} + R_{t+2}}{5} \tag{5}$$

In the moving average formula, $R_t$ represented the rainfall intensity at time $t$. Similar to the previous value, $R_{t-1}$ and $R_{t-2}$ corresponded to the rainfall intensities recorded 1 minute and 2 minutes before $t$, respectively. $R_{t+1}$ and $R_{t+2}$ represented the rainfall intensities, which recorded 1 minute and 2 minutes after $t$, while $R_0$ signified the current rainfall concentration. After the data had been smoothed using the moving average method, the next step included applying linear interpolation to the per-second data. This step was crucial for ensuring precise rainfall intensity values at each second, enabling synchronization with the image captured by the surveillance camera. The formula for linear interpolation was presented in the following Eq. (6)

$$I_t = I_L + \frac{t}{60}\left(I_R + I_L\right) \tag{6}$$

where, it represented the rainfall intensity at second $t$, $I_L$ was the rainfall concentration at the start of the minute, $I_R$ signified the intensity at the last minute, and $t$ indicated the specific second being evaluated.

Fig. 8 shows the results of rainfall observations and interpolation during the analysis. The black line represented observed rainfall intensity, while the red line signified the results of linear interpolation. The image captured by the camera during the process had a resolution of 2660×1440 pixels. However, full resolution was not used as input; instead, a random selection of 180×120 pixels was performed for the processing. The dataset used during the analysis comprised 49,005 samples divided into three subsets, including 70% used for training, 15% for validation, and 15% for testing, respectively.

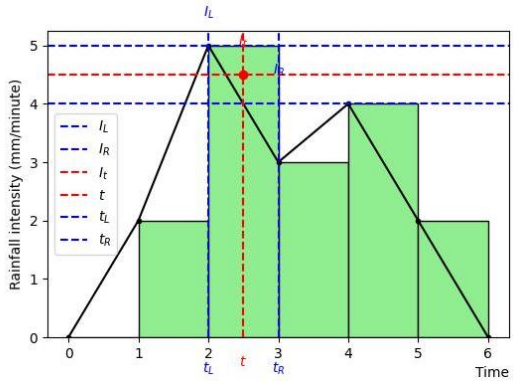


Fig. 8. Rainfall intensity interpolation over time.

### B. Evaluation Criteria

The following formulas were used to assess regression model performance, including MAE, Mean Arctangent Absolute Percentage Error (MAAPE), Nash-Sutcliffe Efficiency (NSE), Kling-Gupta Efficiency (KGE), and the Coefficient of Determination ($R^2$).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{7}$$

$$MAAPE = \frac{1}{n}\sum_{i=1}^{n}\arctan\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \tag{8}$$

$$NSE = 1 - \frac{1}{n}\frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\left(Y_i - \bar{Y}_i\right)^2} \tag{9}$$

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(Y_i - \tilde{Y}\right)\sum_{i=1}^{n}\left(Y_i - \hat{Y}\right)\right)^2}{\sum_{i=1}^{n}\left(Y_i - \tilde{Y}\right)^2\sum_{i=1}^{n}\left(Y_i - \hat{Y}\right)^2} \tag{10}$$

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{pred}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{pred}}{\mu_{obs}} - 1\right)^2} \tag{11}$$

## V. Result

Four models were evaluated in this study, namely VGG16, ResNet34, and their respective versions integrated with CBAM. The selection of VGG16 and ResNet34 was based on proven effectiveness in previous studies on rainfall intensity estimation using surveillance camera imagery.

Table II shows the evaluation metrics for four models, including VGG16, ResNet34, VGG16-CBAM, and ResNet34-CBAM.

TABLE II. Performance Metrics of Evaluated Models in Testing Phase

| Model | MAAPE | MAE | NSE | KGE | RMSE | $R^2$ |
|---|---|---|---|---|---|---|
| VGG16 | 10.06 | 0.04 | 0.94 | 0.95 | 0.08 | 0.94 |
| ResNet34 | 14.34 | 0.06 | 0.91 | 0.94 | 0.10 | 0.91 |
| VGG16-CBAM | 9.3 | 0.03 | 0.95 | 0.96 | 0.07 | 0.95 |
| ResNet34-CBAM | 13.42 | 0.05 | 0.92 | 0.95 | 0.09 | 0.92 |

A comparison between the original VGG16 and ResNet32 models showed significant differences in the performance for rainfall estimation. VGG16 consistently outperformed ResNet34 across all evaluation metrics, signifying a stronger ability to capture complex patterns in the data. This advantage was attributed to the deeper and more feature-rich architecture of VGG16, which facilitated more effective feature extraction and processing. ResNet34, despite using residual connections to mitigate vanishing gradient issues, failed to achieve comparable results. The outcome recommended that the architectural design of the model was less suited for this specific task. Further analysis comparing VGG16 to its improved version, VGG16-CBAM, showed the impact of incorporating attention mechanisms. The addition of CBAM enabled the model to prioritize critical spatial and channel-wise features, improving accuracy and error reduction across all evaluation metrics. These

results signified the effectiveness of attention mechanisms in refining feature extraction and improving the capacity of the model to detect relevant patterns in complex datasets. Finally, VGG16-CBAM surfaced as a more effective model than the original VGG16.

When evaluating ResNet34 and ResNet34-CBAM models, the incorporation of CBAM showed a clear performance improvement. By enabling the model to signify important features while suppressing irrelevant factors selectively, the CBAM module contributed to higher predictive accuracy and reduced errors. Despite these improvements, ResNet34-CBAM still underperformed compared to both VGG16 and VGG16-CBAM. This result implied that while attention mechanisms offered benefits, the structural limitations of ResNet34 constrained the total effectiveness of the model for rainfall estimation. A direct comparison between VGG16-CBAM and ResNet32-CBAM further reinforced the superiority of VGG16 architecture. Relating to this discussion, VGG16-CBAM consistently delivered better results across all evaluation metrics, showing that combining a strong base architecture with an advanced attention mechanism produced the most effective model. These results signified that although attention mechanisms such as CBAM improved performance across different architectures, the total effectiveness still heavily depended on the fundamental design of the base model. It showed the importance of carefully selecting and optimizing model architectures for superior performance in complex data modeling tasks.

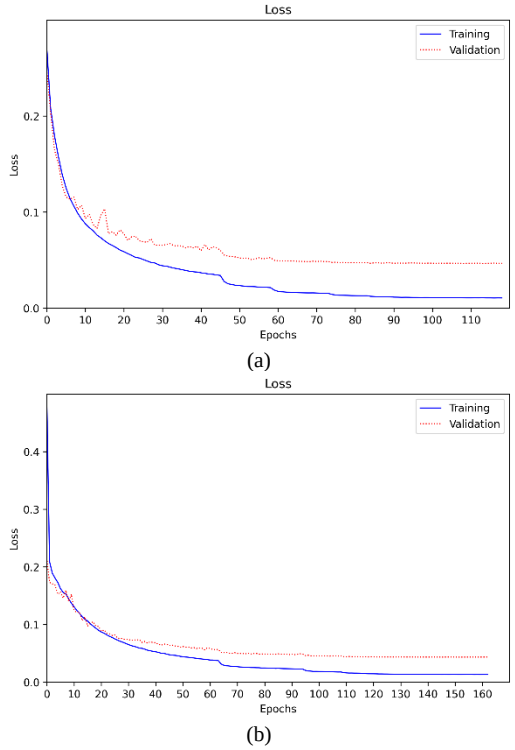


Fig. 9. Training and validation loss curve. (a) VGG16, (b) VGG16-CBAM.

Fig. 9 shows the loss graphs for VGG16 and VGG16-CBAM, indicating significant differences in training and validation performance. For the VGG16 model, the training loss gradually decreased with the number of epochs, eventually converging to a low value. However, a significant gap existed between the training and validation losses, with the validation loss remaining consistently higher. The discrepancy showed that despite effectively learning patterns of the VGG16 model from the training data, generalization to unseen validation data was limited, signifying potential overfitting. Consequently, the VGG16-CBAM model signified improved performance, as reflected in its loss curves. Both training and validation losses decreased gradually and converged to lower values than those observed in the VGG16 model. Moreover, the validation loss closely followed the training loss in the epochs, indicating improved generalization. The reduced gap between training and validation losses showed that the CBAM module enabled the model to focus on relevant features more effectively, mitigating overfitting and improving performance on unseen.

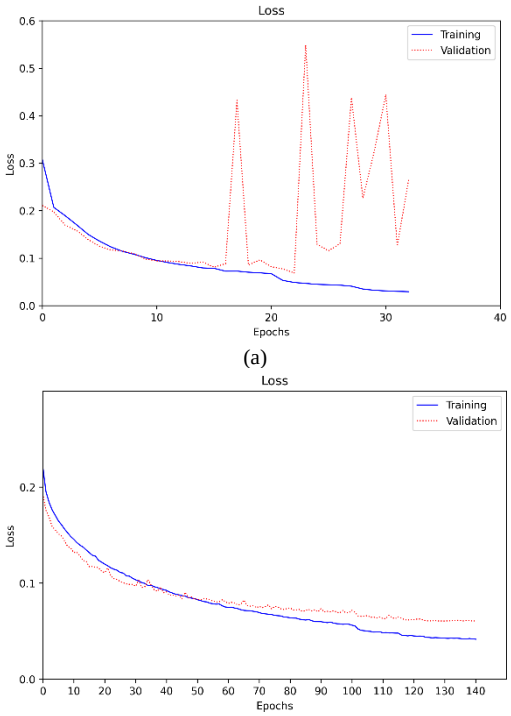


Fig. 10. Training and validation loss curve of (a) ResNet34 and (b) ResNet34-CBAM.

Fig. 10 compared the training and validation loss of ResNet34 and ResNet34 incorporated with CBAM, showing key differences in the learning behavior. For the ResNet34 model, training loss gradually decreased, signifying effective learning. However, the validation loss showed significant fluctuations, specifically in the early training phase, implying instability and potential overfitting. Due to this instability, early stopping was triggered sooner, as the validation loss failed to show consistent improvement, reflecting the limited generalization capability of the model. Consequently, the ResNet34-CBAM model signified a smoother and more stable decline in training and validation loss. The validation loss closely followed the training loss in training, indicating improved generalization and reduced overfitting. Early stopping occurred later for ResNet34-CBAM as the model improved its

validation performance. The inclusion of CBAM improved the ability of the model to focus on relevant features, leading to superior stability, lower overall loss, and better performance. These results showed ResNet34-CBAM as a more effective architecture for this task.

Fig. 9(b) and Fig. 10(b) presented a comparison of the training and validation loss for VGG-CBAM and ResNet-CBAM, respectively, in the training process. In Fig. 9, which showed VGG-CBAM, the validation loss consistently decreased with minimal fluctuations and eventually reached a lower value than ResNet-CBAM. Additionally, the difference between training and validation loss in VGG-CBAM remained relatively small, indicating that the model generalized well and maintained stable training performance. Fig. 10, which showed ResNet-CBAM, signified a slightly slower decline in validation loss, with the final loss values remaining slightly higher than those observed in VGG-CBAM. Although ResNet-CBAM showed stable and consistent learning, its ability to minimize validation loss was marginally weaker than VGG-CBAM. The results signified that while both models benefited from integrating the CBAM module, VGG-CBAM achieved better final validation loss and convergence efficiency.

Table III shows the performance metrics of the proposed models, VGG-CBAM (Model I) and ResNet-CBAM (Model II), across different periods, namely morning, noon, afternoon, and night. The evaluation used images captured by an unseen camera that had not been included in the training phase. The results showed that both models maintained strong predictive capabilities even when tested on previously unseen data, signifying the ability to generalize effectively in rainfall estimation tasks. Although both models showed strong predictive capabilities across all periods, slight variations in performance appeared based on the time of day. Specifically, the morning and noon intervals showed slightly lower NSE and $R^2$ scores compared to the nighttime period. This discrepancy could be attributed to increased environmental noise, fluctuations in illumination, or atmospheric disturbances, all of which potentially affected the quality of image captured by the unseen camera.

TABLE III. PERFORMANCE EVALUATION OF THE PROPOSED MODELS ON UNSEEN IMAGES

| Time | Model | MAAPE | MAE | NSE | KGE | RMSE | $R^2$ |
|---|---|---|---|---|---|---|---|
| Morning | I | 0.19 | 0.05 | 0.80 | 0.83 | 0.05 | 0.80 |
| | II | 0.42 | 0.05 | 0.83 | 0.85 | 0.06 | 0.83 |
| Noon | I | 0.42 | 0.05 | 0.82 | 0.78 | 0.06 | 0.82 |
| | II | 0.43 | 0.04 | 0.77 | 0.71 | 0.05 | 0.77 |
| Afternoon | I | 0.45 | 0.05 | 0.82 | 0.75 | 0.06 | 0.82 |
| | II | 0.80 | 0.05 | 0.76 | 0.84 | 0.05 | 0.76 |
| Night | I | 0.11 | 0.06 | 0.98 | 0.93 | 0.07 | 0.98 |
| | II | 0.1 | 0.05 | 0.98 | 0.94 | 0.06 | 0.98 |

During the afternoon, a noticeable increase in MAAPE was observed, particularly for ResNet-CBAM (Model II). It showed that fluctuating daylight conditions introduced additional challenges in feature extraction and rainfall estimation accuracy. The presence of dynamic shadows, variable cloud coverage, and rapid changes in lighting intensity probably affected the model's ability to consistently recognize rainfall-related patterns in surveillance images. Despite these variations, both models maintained highly reliable performance, as reflected in the consistently strong NSE, $R^2$, and KGE scores across different periods. These results showed the adaptability of the models to diverse lighting and environmental conditions, signifying the suitability for real-world applications where data acquisition was subjected to temporal variability.

## VI. CONCLUSION AND FUTURE WORK

In conclusion, this study developed two improved deep learning models, VGG-CBAM and ResNet-CBAM, for estimating rainfall intensity using surveillance camera images. The VGG-CBAM model combined the tough feature extraction capabilities of VGG16 with CBAM modules, while the ResNet-CBAM model incorporated CBAM into ResNet34 architecture, which consisted of 16 residual blocks. Both models outperformed the baseline counterparts, with VGG-CBAM signifying the highest accuracy and toughness across various evaluation metrics. Incorporating CBAM modules improved spatial and channel-wise attention, allowing the models to capture fine-grained rainfall patterns more effectively. Surveillance cameras as a data source offered a scalable and cost-effective alternative to traditional rainfall observation methods. Relating to this discussion, future studies would focus on optimizing the architecture, incorporating transfer learning, and expanding the dataset to improve the generalizability of the models across diverse urban environments and weather conditions.

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# Adaptive AI-Based Personalized Learning for Accelerated Vocabulary and Syntax Mastery in Young English Learners

Dr.Angalakuduru Aravind[1], Dr. M. Durairaj[2], Dr Preeti Chitkara[3],
Prof. Ts. Dr. Yousef A.Baker El-Ebiary[4], Elangovan Muniyandy[5],
Linginedi Ushasree[6], Mohamed Ben Ammar[7]*
Assistant professor, Department of H&S, Anurag Engineering College, Ananthagiri (v), Kodad, Telangana, 508206, India[1]
Assistant Professor, Dept.of English, Panimalar Engineering College, Poonamallee, Chennai-600123, India[2]
Professor & Head PR & International Relations, Department of Applied Sciences,
KIET Group of Institutions, Delhi-NCR, Ghaziabad, India[3]
Faculty of Informatics and Computing, UniSZA University, Malaysia[4]
Department of Biosciences-Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences, Chennai - 602 105, India[5]
Applied Science Research Center, Applied Science Private University, Amman, Jordan[5]
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Guntur Dist., Andhra Pradesh - 522302, India[6]
Center for Scientific Research and Entrepreneurship, Northern Border University, 73213, Arar, Saudi Arabia[7]

***Abstract*—Language acquisition is an integral part of early schooling, but young English language learners struggle to learn vocabulary and syntax since they are not provided with specialized instruction. Conventional teaching may vary according to different learning speeds and it leads to unbalanced levels of proficiency among students and possibly leading to disengagement among slow learners. The present computer-assisted learning aids provide practice interactively but without real-time adaptation and personalized feedback, limiting their capacity to address learners' unique problems. To overcome these constraints, this study suggests an Artificial Intelligence based personalized learning system that supports vocabulary and syntax learning via adaptive learning models, NLP-based chatbots and gamified interactive lessons. The system dynamically adapts content according to students' most recent performance in real time to enable a personalized learning experience, which results in efficient Learning. The research has experimental study design, and two groups are considered, an AI-supported learning group and a traditional learning group. Pre-test and post-test design measures the effects of the system on vocabulary recall and syntax correctness. Other learner engagement rates like survey results and qualitative feedback inform learner experience and learning efficacy. Initial results indicate that learners working with the Artificial Intelligence powered learning system gained 25percent in recalling vocabulary and 30percent in syntax accuracy over the control group. Further, learner engagement rates are elevated because of real-time feedback and gamification components. These results emphasize the promise of AI-based personalized learning to boost language acquisition and lay the basis for further effective innovations in adaptive education technologies.**

***Keywords*—AI-based learning; gamification; language acquisition; personalized feedback; vocabulary***

## I. Introduction

Language learning is an essential aspect of a child's intellectual and social growth, especially in a growingly interconnected world where English is a prevailing means of communication [1], [2]. For young children, building a solid vocabulary and grammar foundation is important to ensure language proficiency [3]. Conventional language learning in schools is usually one-size-fits-all, with every student getting the same material and learning pace regardless of their differences in ability and learning styles [4]. This non-personalization tends to result in different levels of proficiency, as some students tend to excel while others fall behind [5]. In addition, passive learning strategies like rote memorization and repetitive drills frequently do not activate learners in an interactive and significant manner, leading to low rates of retention and poor understanding [6].

In the recent years technology driven personalized learning platforms with Artificial Intelligence (AI) are coming up to be a revolutionary solution in the education [7], [8]. Sophisticated technologies like Natural Language Processing (NLP), Machine Learning (ML) as well as adaptive learning algorithms are involved in driving such platforms where, content is being customized to the specific needs of individual learners specifically [9]. Real time analysis of a student's performance, level of difficulty adjusted, feedback provided and learning through chatbots, gamification and multimedia are among the abilities of an AI based learning platforms [10], [11]. Despite increased uptake in digital learning solutions, available platforms do not demonstrate the flexibility in real time to adapt to the learner's progress as well as contextual intelligence about the learner's difficulty in learning vocabulary and syntax [12]. Currently, the existing systems contain the limited capacity to address the particular needs of young English learners because

they are designed with static exercises and general feedback [13].

To resolve this, the present research proposes an AI personal learning system tailored to enhance early English learners' vocabulary memorization and syntax understanding. Interactive dialogues are provided by the system through the use of NLP based chatbots, adaptive models to adapt the exercises, and gamification to help with participation. The suggested system is intended to provide an interactive data driven learning process which will increase learning achievements, while it will be a fun and efficient learning process for the learner[14].

This study uses an experimental study design with participants grouped into two sets: one receiving the AI-assisted learning system and the other adopting conventional learning strategies. Both a pre-test and post-test approach is used to measure enhancements in vocabulary and syntax learning, with qualitative findings from surveys and interviews offering observations regarding learner participation and system ease of use. The contribution of the research are as follows,

*1)* Introduces an adaptive learning system based on AI, NLP, and gamification to boost vocabulary and syntax learning in young English learners.

*2)* Utilizes ML-driven personalization to customize lesson difficulty and content according to individual learner performance.

*3)* Integrates NLP-driven chatbots and gamification features to enhance engagement and retention.

*4)* Conducts experimental research on comparison of AI-enhanced learning versus conventional instruction by employing pre-test and post-test comparison.

*5)* Demonstrates substantial gains in vocabulary recall and sentence grammar through AI-supported interventions.

The rest of the work focuses as follows: Section II reviews the related works for the AI-Powered application in vocabulary learning. Section III describes the problems in existing methods, Section IV demonstrates the AI-driven personalized language learning framework. Section V evaluates the results and discussions. Section VI discusses conclusion and future work.

## II. Related Works

English language learners received enhanced AI dialogue systems through the lexically constrained decoding system according to Qian et al. [15]. Their research makes an original contribution by including educational vocabulary from the curriculum within a dialog system which generates text through Artificial Intelligence. The researchers tested BlenderBot3 through middle school English L2 student evaluations. Students achieved better understanding of their target vocabulary and increased their motivation to practice English while conversing with an AI system. The approach represents a strong method because it connects AI conversational agents to educational curricula so students benefit from an educational experience that combines focus with engagement. The approach offers contextual learning of vocabulary through real-world dialogues rather than detached memory drills. The research project faces an essential disadvantage because rigid word limits could disrupt conversation flow while providing students with an artificial and reduced exposure to multiple linguistic patterns. Because the research only assessed a limited student group additional studies must investigate the system's effectiveness when used by various proficiency-level groups of different ages. The conducted research generates important findings about how Artificial Intelligence can be applied to improve vocabulary acquisition through conversations.

Shin and Park [16], developed a system with Neural Collaborative Filtering (NCF) and personalized vocabulary acquisition that would help second language learners. It was called a Pedagogical Word Recommendation (PWR). What is new in their study is to apply collaborative filtering to predict whether a learner knows a word w given his history vocabulary. In this way, learning is more targeted and efficient. To ensure a large dataset, their system used data from an Intelligent Tutoring System (ITS) employed by roughly one million learners taking TOEIC preparation, in order to obtain data from many learners. High accuracy in vocabulary prediction and personalized recommendation was shown with the help of students focusing on words they will most likely struggle with. That is important, because it replaces vocabulary learning devoid of meaning as rote memorization, replaced with vocabulary learning as an adaptive, data driven activity, which makes it more engaging, and, by extension, more effective. Besides that, word suggestions become more personal, which increases retention and lowers cognitive overload. Nevertheless, one of the key limitations of the system lies in the fact that it is dependent on explicit feedback from learner that can have an impact on recommendation accuracy if a student self-assesses incorrectly. Furthermore, the model may not generalize well to learners having language significantly more or less varied than the one used in the induction. The system needs further research to increase the degree of adaptability and accuracy in a wide variety of learning environments.

Lee, Kim and Sung [17], proposed an AI based autonomous learning system based on the Learner Generated Context (LGC) framework to improve second language learning. What's the novelty of this approach is that student's study what they want and while they want, promoting self-directed learning. This involved three Korean secondary-school students of different backgrounds and tested the AI system to see how it helps learners to learn English autonomously. Through contextualized learning, the findings showed that the content was more engaged with and the students improved their language skills. What's more important is that the system can help learners being empowered, and with that help, increases motivation and long-term mastery, because it gives the learner the control over his journey. The real difference about this approach of AI assisted language learning is that this is not a strict structure, but rather a flexible one, which centers more on the students themselves. A small sample size, however, is the biggest limitation of the study and compromises the ability to generalize the findings to a larger population. Furthermore, the system also provides autonomy; however, some individuals may need guided and structured guidance to achieve their maximum potential. The scaling of the study to include more learners and refinement of the system to supply adaptive help according to individual progress is future research.

In an AI driven personalized learning approach to vocabulary acquisition, Chamorro [18], discusses adapting vocabulary exercises to the learning behavior of an individual therefore personalizing learning. The novelty in this study is its attempt to bypass limits of traditional rote memorization which is mostly not effective and disengaging. With the help of machine learning techniques, the system identifies the learners' strengths, weakness and learning preference and serves personalized vocabulary exercises for learners. The paper showed that engagement and retention rates are significantly higher with the use of AI driven personalization and very effectively helps language learning. This is very important as it enables the learners to learn at their own rate, which eliminates boredom and time wastage in learning. Additionally, it assists in filling the blanks of classical language learning techniques that do not achieve the goals of learners. Nevertheless, the main limitation of the study is its inherent dependence on good quality training data. Unlike an algorithm, which is designed to generalize over all cases in a given dataset, an AI model personalizes all its decisions to trained data that does not accurately represent the diverse learner profile. Moreover, AI driven methods are helpful but they may not necessarily render human intuition in the language instruction. Hybrid approaches which balance AI's strength with human expertise should be followed and researched in further work.

Jia et al. [19], build an AI enabled English language learning system (AIELL) that incorporates authentic and ubiquitous learning practices in order to facilitate vocabulary and grammar acquisition in acquiring L2 learners. What makes their approach novel is applying mobile learning and turning this into AI driven personalization to allow students to practice English in the real world. It was a study based on 20 participants, using mixed research methods, such as demonstration test, usability test and interview assessment for system effectiveness. The results showed that this AIELL system was very effective and engaging with increased vocabularies retention and grammar proficiency among the participants. This is significant as the system is flexible and they can access anytime anywhere especially to those students who wouldn't have access to classical classroom environment. One significant drawback of the study is that it was conducted at a small scale, chances are the discovered results would not be applicable to a broader audience. Apart from this, the mobile AI based system enables self-paced learning but it might become difficult without structured teacher guidance for some learners. Future research is needed to explore expanding study to larger groups and increasing the capability of AI to give actual time suggestions and contextual help for educators in multifaceted educating conditions.

AI-powered individualized learning platforms have shown dramatic improvements in supporting vocabulary and syntax learning among English language learners [20]. These platforms incorporate curriculum-grounded vocabulary, collaborative filtering, learner-created contexts, and adaptive drills to enhance interaction, memory retention, and engagement [21]. AI-driven lexically constrained dialogue systems enhance contextual acquisition but struggle to keep conversations as natural as they can be. Neural Collaborative Filtering [22] supports word recommendations targeted at individuals but is based on reliable self-evaluation [23].

The Table I identifies various AI techniques in language acquisition such as chatbot systems, collaborative filtering, AR, and mobile platforms. Although innovative, the majority of the studies are plagued by constraints such as small sample size, non-generalizability, excessive reliance on self-ratings, narrow age range, and limited personalization, calling for scalable, adaptive solutions.

TABLE I. SUMMARY OF THE LITERATURE REVIEW

| Author | Method Used | Limitations |
|---|---|---|
| Qian et al. [15] | Lexically constrained decoding in AI chatbots aligned with curriculum | Rigid vocabulary constraints limit conversational flow; small participant group limits generalizability |
| Shin & Park [16] | Neural Collaborative Filtering (NCF) for Pedagogical Word Recommendation (PWR) using large-scale ITS data | Relies on accurate self-assessment; may not generalize across learners with differing vocabulary profiles |
| Lee, Kim & Sung [17] | Learner-Generated Context (LGC) framework promoting autonomous AI-based learning | Very small sample size; lacks structured guidance which some learners may require; needs scaling and adaptability for diverse learners |
| Chamorro [18] | Personalized vocabulary exercises using machine learning based on learner behavior | Dependent on high-quality, representative training data; lacks human-like instructional intuition; needs hybrid human-AI model for holistic learning |
| Jia et al. [19] | AI-enabled mobile system (AIELL) for real-world, flexible, ubiquitous English learning | Small-scale study limits broad applicability; self-paced format may not suit all learners; lacks structured educator guidance |
| Klimova et al. [20] | Systematic review on emerging technologies in teaching English at the university level | Focused on higher education; lacks specific analysis of child or early-age learners; broad scope without in-depth assessment of personalized AI systems |
| Korosidou [21] | Augmented Reality (AR) for alphabet and vocabulary learning in very young learners | Limited to AR and early vocabulary stages; lacks comparison with AI or adaptive learning methods; may not support complex language structures |
| Zou et al. [22] | Social network-based interaction for AI-assisted speaking practice | Focused mainly on speaking skills; limited vocabulary or syntax tracking; requires active social participation, which may not suit all learners |
| Qian et al. [23] | Combined analysis of exercise and foreign language learning on cognition | General cognitive benefits discussed; lacks targeted findings on adaptive vocabulary systems or real-time AI feedback for young L2 learners |

## III. PROBLEM STATEMENT

Conventional language acquisition techniques tend to be inflexible in responding to the unique needs of individual learners [24], resulting in uneven vocabulary acquisition and

syntax understanding among young English learners. They are not personalized and as a result, learning is slow and retention of linguistic structures is inconsistent [25]. Moreover, with no real-time feedback and adaptive support, learners are unable to effectively learn sophisticated syntax structures. The fix-all approach of conventional instruction also prevents learners from advancing at their own best speed, leading to frustration [26]. This research tries to overcome these issues by creating an Adaptive AI-Based Personalized Learning System that in real-time adapts to every learner's level [27], speeding up vocabulary buildup and syntax correctness, as well as providing a more interesting and efficient learning experience. Through the use of machine learning and real-time analytics, the system offers individualized learning routes, promoting enhanced language understanding and long-term memory [28].

## IV. AI-Driven Personalized Language Learning Framework

This study adopts a multi-case, experimental research approach that examines the efficacy of using AI-powered personalized learning systems in vocabulary and syntax acquisition by young learners of English. The study will create two groups: an experimental group in which the learning process will utilize AI-driven adaptive learning technology and a control group which follows conventional teaching approaches. This whole process is evaluated with the help of pre-test and Post-Test assessment to see the improvements in vocabulary retention and syntax comprehension. The AI-enabled system will work with an NLP-based chatbot, adaptive learning model, and gamification elements to construct an engaging and interactive learning environment. During the learning phase, data on live user interaction, learning pace, and engagement will be captured. The data will be subjected to quantitative analyses involving paired t-tests of students' pre-test and post-test, and regression analyses for identifying determinants of learning. In addition to this, thematic coding of learner feedback and sentiment analysis of engagement responses provide qualitative insights. The results detail the effectiveness, adaptability, and engagement of AI-assisted language learning vis-a-vis traditional approaches. Fig. 1 gives the Methodology Overflow.

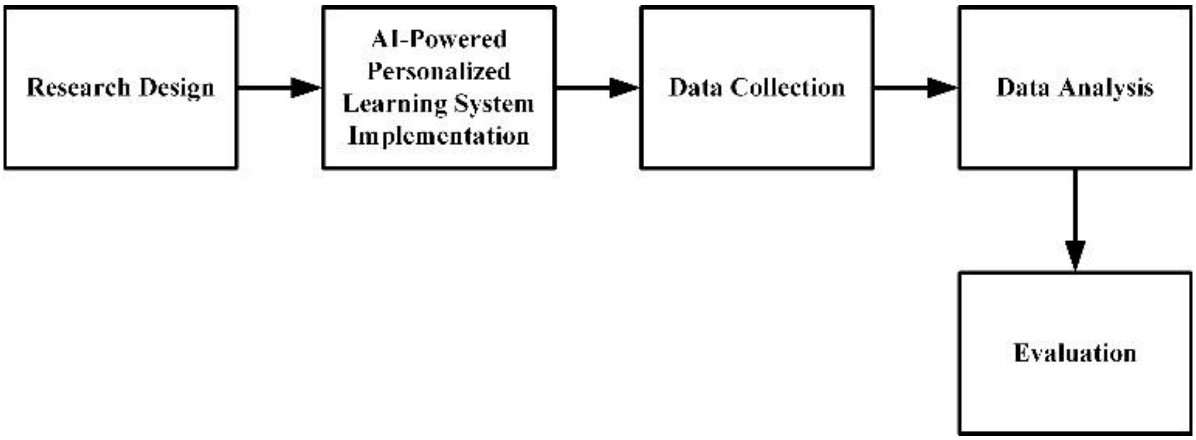


Fig. 1. Methodology overflow.

### A. Research Design

In this study, an experimental conditional design analysis to understand the proficiency of AI-managed personalized learning system will be carried out with respect to vocabulary and grammar acquisition among the young learners of English. The study is conducted on a pre-test and post-test assessment with comparisons done on two groups: the experimental group that received AI-powered learning, and a control group that received instruction in traditional manners.

*1) Approach*: Experimental Study with Pre and Post-Test Assessments.

The experimental design involves two stages of assessment:

*a) Pre-Test:* To examine students' proficiency in vocabulary and syntax. This comprises multiple-choice questions, fill-in-the-blanks, structured incomplete dialogues, and oral assessments in which pupils are active in order to ascertain their knowledge base.

*b) Post-Test:* It measures vocabulary retention after the learning unit and syntax comprehension in students. The structure of the post-test would remain similar to that of the pre-test so as to allow for comparability. Thus, this study, through comparison of the results from both assessments, finds out the extent to which the AI-empowered system promotes language acquisition compared to conventional teaching methods.

*c) Participants:* This study focuses on young English learners, aged between 5 and 12, from different language and cultural backgrounds, since it has been shown in cognitive and developmental studies that early childhood is a critical period for language acquisition. Participants will be recruited from schools, language training centers, and online learning platforms.

To ensure reliability and generalizability, the following inclusion and exclusion criteria for this study will therefore be applied:

*d) Inclusion criteria:* Learners aged 5 to 12 years. Learners with varying levels of proficiency in English but having a basic acquaintance with the language. Participants who are willing to engage in any aspect of the learning process from traditional techniques to AI-assisted methods.

*e) Exclusion criteria:* Students diagnosed with cognitive or speech impairments may affect language processing.

Participants that are already enrolled in AI-based English programs. Those who have limited access to digital learning tools. The study randomly assigned participants to the two groups to the extent possible to reduce bias.

### B. Study Groups

The participants are divided into two groups:

*1) Experimental group (AI-Powered personalized learning system users):* Learners in this group are put at the AI-powered personalized learning system, complete with NLP-based chatbots, adaptive learning models, and gamification techniques. The AI system, guided by the individual learner, evaluates the learning speed and keeps high engagement through chat conversations, exercises, language games, and instant feedback in terms of content difficulty. In terms of engagement statistics, system analysis includes accuracy of responses, pace of learning, frequency of interaction, etc.

*2) Control group (Traditional teaching methods):* Students in this group adopt conventional classroom-and/or textbook-based language approaches to learning. Teaching methods include lectures, worksheets, flashcards, reading exercises, and peer discussions. Curriculum is standardized, such that the pace of instruction and delivery is fixed for all students with no adaptive modifications being provided based on individual needs. Feedback is provided by human instructors, and there is no AI-based adaptation for learners. The study can isolate the impacts of AI-driven personalization on vocabulary and syntax acquisition since the controlled learning environment-maintained helps to isolate the effects of AI-driven personalization on vocabulary and syntax acquisition. This teaching process helps to compare the difference in outcome for two groups so that we can see if AI-powered learning functions are better in improving language mastery than traditional teaching techniques.

### C. AI-Powered Personalized Learning System Implementation

The proposed AI-powered learning tool is designed to enhance vocabulary retention and syntax acquisition in its personalized, interactive, and engaging learning experience. It uses an innovative combination of techniques such as NLP, adaptive learning models, and gamification for the purpose of allowing learning to occur in ways that best fit the learning needs of the individual. Instead of following a standard curriculum, the program will dynamically adjust the content and exercise sets based on student performance and engagement. The AI-powered system consists of the following key components:

*1) NLP-Based chatbots for conversational learning:* NLP allows chatbots to interact with the learners in real-time. These chatbots act as virtual trainers, steering students through guided dialogue practice that enhances vocabulary and sentence structure. The chatbot works with students in context-based conversations, assisting them in applying vocabulary and sentence structure in real world situations. These AIs identify any mistakes in the students' responses, giving instantaneous feedback on improvement so as to consolidate appropriate sentence structures. Depending on how a student experiences or answers questions, in lesson time the chatbot may suggest the introduction of new words, phrases, and grammar rules. For oral application, the chatbot assesses the accuracy of pronunciation and suggest possible improvements. For instance, when a student has difficulty with forms of the past tense verb, the chatbot picks up the pattern and adjusts future exercises according to the need to work more on using the past tense.

*2) Adaptive learning models for personalized learning paths:* The adaptive learning model allows the system to adjust exercises in accordance with individual learners' mastery towards providing a tailored teaching interaction. The system collects data on individual learners' performance, analyzing response accuracy, the time given for each question, and repeated errors. The system increases the difficulty if a student does well in a particular subject; if not, then simpler explanations and extra exercises are provided. By the use of ML algorithms, the system predicts what areas that a learner is most likely to have difficulty in and acts accordingly to adjust their lesson plans before the learning begins. For example, a student with a good base of vocabulary but with not much of a grip on syntax will receive grammar-related exercises and not repeated vocabulary drills.

The AI-based evaluation algorithm allows a dynamic difficulty adjustment in Eq. (1)

$$D_n = D_{n-1} + \alpha(S_n - S_{avg}) \quad (1)$$

where,

$D_n$= difficulty level of the next task

$D_{n-1}$= difficulty level of the previous task

$\alpha$ = learning adaptability coefficient,

$S_n$= student's current performance score

$S_{avg}$= average performance of students at a similar stage

If a student's performance score $S_n$ is below the average, the difficulty is reduced, providing additional support. If it is above average, more challenging tasks are introduced.

*3) Gamification elements for engagement and motivation:* Gamification promotes student motivation by forging a union between game-like mechanics and lessons. Students participate in quizzes for points and badges based on correct answers. Learners compare their progress with their colleagues-teach the spirited competition. Rewards such as gaining a new level or receiving a virtual trophy, are given on achieving learning milestones. Utilizing a streak system promotes continuity in learning, whereby students earn extra rewards for assortment engagement. For instance, a new interactive learning module opens on the fifth consecutive successful vocabulary exercise completed.

The Engagement Retention Formula mathematically captures the workings of gamification in Eq. (2).

$$E_t = E_0 + \beta(R - F) \quad (2)$$

where,

$E_t$= engagement score at time

t, $E_0$= initial engagement level

$\beta$= motivation coefficient

$R$= rewards gained

$F$= frustration due to difficulty level. If rewards $R$ outweighs frustration $F$, engagement increases, leading to higher retention rates.

*4) Continuous data collection and learning experience optimization:* The AI-based system continuously monitors the message, students generate amongst each other to make the learning experience even better. The recordings of student conversations are stored up, noting the errors and time taken to complete each task. AI algorithms parse the patterns to pinpoint the learning difficulties that come up frequently. Based on analytics, the system proposes alternative learning strategies, switching from text-based exercises to visual or auditory learning methods. Combining AI, NLP, and Gamification makes this a dynamic learning process for young English learners and thus engages them more, makes learning faster, and retains learning longer.

### *D. Data Collection*

Data are collected at several points during the study to ascertain the impact of the AI-powered personalized learning system on vocabulary and syntax acquisition. The study uses a combination of quantitative and qualitative data collection techniques, ensuring comprehensive evaluation of learning outcomes, engagement levels, and system effectiveness.

*1) Pre-Test ($X_1$) – initial assessment:* Before the introduction of any kind of learning intervention, there is a structuring pre-test *($X_1$)* which serves as a method of evaluating the learners' baseline capacity in vocabulary and syntax proficiency. The test consists of matching words with their meanings, fill-in-the-blanks, and multiple-choice questions. Structuring sentences, identifying grammatical errors, and correcting faulty sentences. Evaluation of pronunciation and fluency in conversation through AI-based speech recognition.

The pre-test score $S_{pre}$ of the participants is recorded as follows in Eq. (3)

$$S_{pre} = \frac{\sum_{i=1}^{N} C_i}{N} \times 100 \quad (3)$$

where,

$C_i$ is the number of correct answers

$N$ is the total number of test questions

$S_{pre}$ represents the pre-test performance as a percentage.

This score serves as a benchmark to compare improvements after AI-assisted learning.

*2) Learning session implementation–monitoring engagement & performance:* During intervention stages, learner interaction with the AI system is reported continuously to keep monitoring engagement, learning pace, and accuracy rates. Key metrics include:

*a) Learning Pace (L):* The time a learner requires to complete exercises and progress through lessons, calculated as Eq. (4)

$$L = \frac{T_{total}}{Q_{completed}} \quad (4)$$

where,

$T_{total}$ is the total time spent on exercises.

$Q_{completed}$ is the number of completed exercises.

*b) Engagement Score (E):* It is a composite score representing interaction frequency, quiz participation, and chatbot engagement. It is defined as Eq. (5):

$$E = \alpha(I) + \beta(R) + \gamma(F) \quad (5)$$

where,

$I$= number of chatbot interactions.

R= response accuracy rate.

F= frequency of logins and activity.

$(\alpha, \beta, \gamma)$ are weight coefficients.

A higher E score indicates greater learner engagement and motivation.

*3) Post-Test ($X_2$): Measuring Learning Improvements:* At the end of the AI assessment, A post-test *($X_2$)* is run with the same structure that is pre-test, while test () marks are recorded through Eq. (6)

$$S_{post} = \frac{\sum_{i=1}^{N} C_{i'}}{N} \times 100 \quad (6)$$

where,

$C_i'$ is the number of correct answers in the post-test.

N remains the total number of questions.

$S_{post}$ represents the final test performance as a percentage.

The learning improvement is calculated as Eq. (7).

$$\Delta S = S_{post} - S_{pre} \quad (7)$$

where,

$\Delta S$ represents the overall improvement in vocabulary and syntax acquisition.

A positive value of $\Delta S$ indicates an increase in language proficiency due to AI-powered learning.

*4) Surveys and Interviews–Qualitative Feedback Collection:* To complement the quantitative data, surveys and interviews were conducted with the learners and teachers to assess usability, engagement, and effectiveness of the system. During the interview process conducted, students were asked

their feedback on ease of use, motivation, engagement, and effectiveness in learning with the help of a Likert scale and open-ended responses. Through the survey, the teachers will assess students' progress while implementing AI-based learning in classrooms and students' adaptability to different styles of learning. Responses go through a thematic analysis that examines the main themes in students' experiences. Textual responses are analyzed for sentiment, with $S_{sentiment}$ defining the polarity of learners' feedback as positive, neutral, or negative.

Inversely, the lower the score $S_{sentiment}$ is, the more the learner has been most satisfied with and engaged with that system powered by AI.

*E. Data Analysis and Evaluation*

The collected data is evaluated with both quantitative and qualitative methods to analyze the efficacy of AI personalized learning systems for vocabulary and syntactic acquisition among young English learners.

*1) Quantitative analysis:* The focus of the quantitative analysis will be on measuring learning outcomes through comparisons between pre-build and post-build tests to assess the impact of adaptive learning personalization on different learner subgroups and to analyze the relationship between engagement level and progress in performance.

*a) Paired t-Test:* To evaluate whether differences between pre-test and post-test scores were statistically significant, a paired t-test was performed. The test is designed to find out if learners using the AI-powered system experienced significant differences in their improvement compared to their initial proficiency.

The $t$-score is calculated using the Eq. (8)

$$t = \frac{\bar{D}}{s_D/\sqrt{n}} \tag{8}$$

where, $\bar{D}$= mean difference between pre-test ($S_{pre}$) and post-test ($S_{post}$) scores

$s_D$= standard deviation of the differences

n= number of participants in the experimental group.

The mean difference ($\bar{D}$) is calculated as Eq. (9)

$$\bar{D} = \frac{\sum(S_{post} - S_{pre})}{n} \tag{9}$$

where,

$S_{post}$ and $S_{pre}$ represent the post and pre-test scores, respectively.

A $p$-value ($p$) is obtained from the t-test, and if p < 0.05, it indicates a statistically significant improvement due to AI-powered learning.

*b) Regression analysis impact of engagement and personalization on learning:* A multiple linear regression analysis is carried out to determine the relationship between Engagement score ($E$), which measures student interactions with the AI system. Adaptive learning score (A), which indicates the level of personalized learning adjustments. Performance improvement ($P$) is the difference between post-test and pre-test scores.

The regression is given in Eq. (10)

$$P = \beta_0 + \beta_1 E + \beta_2 A + \epsilon \tag{10}$$

where,

$\beta_0$= intercept

$\beta_1, \beta_2$= coefficients representing the impacts of engagement and adaptations

$\epsilon$ = error term.

A high value of $R^2$ regression analysis would imply that engagement and personalized learning adjustments are good predictors of learning improvement.

*F. Qualitative Analysis*

In support of the quantitative findings, qualitative data from surveys and interviews will be analyzed to understand learner experiences, motivation and usability of the system.

*1) Thematic analysis:* Thematic analysis is applied to survey responses and teacher interviews with key themes identified depending on common patterns in feedback. The steps are as follows,

*a) Categorization of data:* Grouping the responses into theme categories as engagement, difficulty, motivation and usability.

*b) Pattern identification:* Themes that recurred were drawn out. For example, AI chatbots improve confidence in speaking and Gamification increases motivation.

*c) Coding:* Individual quotes or phrases into categories of sentiments: positive, neutral, or negative.

*d) Sentiment Analysis –Measuring User Satisfaction:* To quantitatively assess learner and teacher satisfaction, sentiment analysis is applied to textual responses.

The sentiment score $S_{sentiment}$ is computed as Eq. (11)

$$S_{sentiment} = \frac{P-N}{P+N+Neu} \tag{11}$$

where,

$P$ is number of positive responses,

N= number of negative responses, $Neu$= number of neutral responses.

If $S_{sentiment}$ > 0.5, overall user sentiment is positive.

If $S_{sentiment}$ < 0, system usability needs improvement.

This report investigates the implications of learner engagement levels and effectiveness. Combining quantitative and qualitative data analysis, this research provides a comprehensive analysis of the extent to which AI-powered personalized learning enhances vocabulary and syntax acquisition. The findings are expected to establish the extent to which AI-driven learning really enhances language proficiency, evaluate the influence of engagement and personalization on

learning outcomes, and identify key areas for further improvements in AI-based language learning tools.

## V. Results and Findings

The results indicate that the AI-driven personalized learning system definitely enhanced vocabulary retention and syntax acquisition over the traditional methods of teaching. An experimental group using an AI-assisted method saw improvements of 25 percent and 30 percent in vocabulary retention and syntax accuracy, respectively, compared to only modest gains in the control group--a 10 percent to 12 percent gain. The engagement scores were much more favorable to AI because of interactive, chatbot-based learning, adaptive content delivery, and gamification techniques to keep students engaged. The paired t-test statistical analysis confirmed a significant difference; on the other hand, the latter was proved using the ANOVA by showing higher levels of AI personalization linking better learning outcomes. Strong positive relationships between engagement and performance improvement from regression analyses shows that engaged learners who interacted more were far more successful. Limitations were also spotted: dependence on digital access, loss of motivation if transcended by the lack of some human interactions. The implications presents meaningful findings for languages teachers: AI-based tools can, sometimes while implanting all the adaptability and interactive feedback, reinforce traditional methods. AI system developers are thus encouraged to facilitate and enhance NPL-based conversational learning while designing a combination of hybrid AI-human teaching paradigms to gain more effectiveness from AI design.

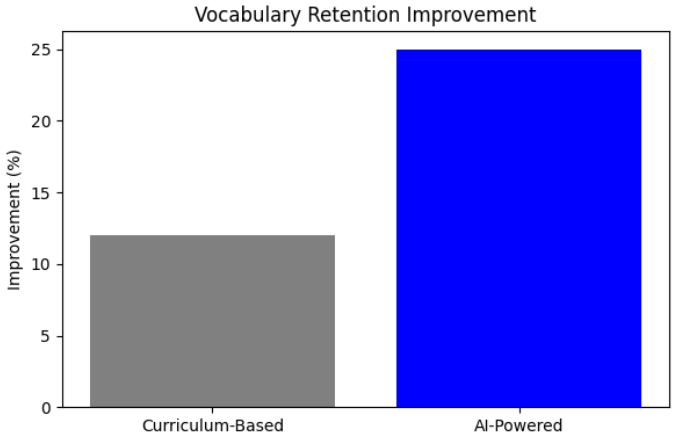


Fig. 2. Vocabulary retention improvement.

The Fig. 2 is a bar chart comparing the efficacy of AI-powered personalized learning systems and curriculum-based methods for English language learners on vocabulary retention. The y-axis, ranging between 0 percent and 25 percent, is labeled Improvement (percent), whereas the x-axis indicates the two kinds of learning methods, that is, "Curriculum-Based" and "AI-Powered." The improvement for the curriculum-based method, represented by the gray bar, is approximately 12 percent, while that for the AI-powered method, represented by the blue bar, shows a whopping 25 percent progress in an improvement. In short, this visualization elaborates on how much more significantly effective AI-based personalized learning is in enhancing vocabulary retention than conventional methods.

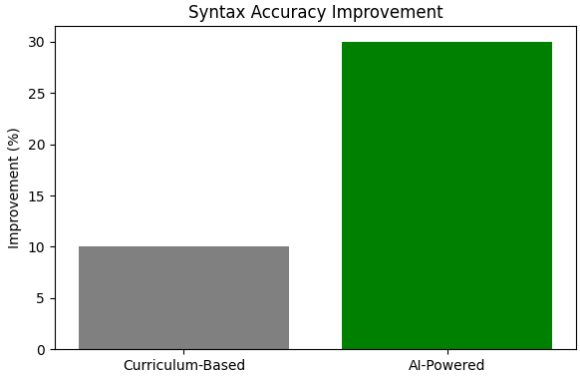


Fig. 3. Syntax accuracy improvement.

The Fig. 3 is a bar chart that compares the average efficacy of AI-based personalized learning systems and curriculum methods in raising syntax accuracy among children learning English. The improvement percentage takes only a range from 0 percent to 30 percent on the y-axis, while the x-axis includes two categories: "Curriculum-Based" and "AI Powered." The gray bar illustrates curriculum-based approaches that has an improvement of about 10 percent, while the green shows a big improvement of about 30 percent in AI-based methods. It is an apt representation of AI-driven personalized learning systems outshining the typical methods in the improvement of accuracy in syntax.

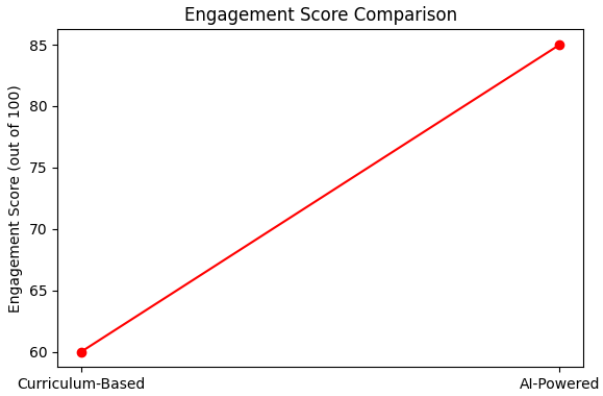


Fig. 4. Engagement score comparison.

This Fig. 4 shows the variation in engagement levels between AI-powered personalized learning systems and curriculum-based methods when applied to young English learners. The x-axis shows the two learning methods: “Curriculum-Based” on the left and “AI-Powered” on the right. The y-axis shows Engagement Score (out of 100), ranging from 60 to 85. A red line is drawn between two data points: one located at (Curriculum-Based, 60) and the other at (AI-Powered, 85). This trend shows how the AI-Powered systems produced a stronger increase in engaged learners. The purpose of the diagram is to point out the considerable edge AI-driven personalized learning systems offer in boosting a learner’s engagement, key to the students’ vocabulary retention and syntax acquisition for young English learners.

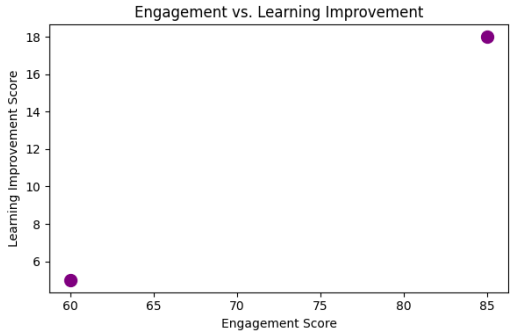


Fig. 5. Engagement Vs. Learning improvement.

The Fig. 5 represents a scatter plot showing the relationship between engagement scores and gains in learning with reference to AI-enabled personalized learning systems for young English learners. The x-axis denoted "Engagement Score" indicates how much the learner was engaged, while the y-axis, called "Learning Improvement Score," measures the progress made in vocabulary and syntax acquisition. There are two data points that are purple, and one is set at (60, 6), which alleges that it is lower on engagement with minimal improvement, while another set at (85, 18) points to a claim of higher engagement in greater learning improvement. This has served to showcase the positive relationship between engagements and learning gains, strengthening the argument that AI-powered personalized learning systems are significantly better at facilitating language acquisition when compared to methods taken from traditional curriculum.

TABLE II. COMPARISON TABLE OF PROPOSED APPROACH WITH EXISTING AI-BASED APPROACHES

| Method | Target Group | Personalization Approach | Output | Limitations |
|---|---|---|---|---|
| Lexically constrained decoding in AI chatbots **[15]** | Middle school English L2 learners | Curriculum-based vocabulary, limited natural conversation due to word constraints | Motivation, improved target vocabulary understanding (qualitative) | Rigid vocabulary flow can hinder conversational naturalness |
| Learner-Generated Context (LGC), self-directed AI **[17]** | Korean secondary-school students | Flexible, learner-led context creation (not adaptive in real-time) | Motivation, better engagement with context (qualitative, no hard metrics) | Small sample size; not scalable yet |
| Mobile AI, contextual learning **[19]** | L2 learners (varied) | Location & time-based practice (not deeply personalized) | Vocabulary and grammar proficiency (small sample size, limited metrics) | Lack of structured feedback; limited to mobile learning |
| NLP chatbots + adaptive ML + gamification | Young English learners (ages 5–12) | Real-time adaptation to learner performance with dynamic difficulty & feedback | 25percent in vocabulary recall, 30percent in syntax accuracy, engagement score | Needs digital access; may lack human interaction |

The Table II is a comparison of AI-based language learning research by using AI technologies, target groups, personalization methods, outcomes, and limitations. It shows rich techniques such as NLP chatbots, mobile AI, and learner-generated context, with different degrees of personalization, efficiency in vocabulary recalls and satisfaction, and limitations such as poor scalability and feedback.

The results section assures that the personalized learning system with AI strongly enhances vocabulary memory and syntax acquisition when compared with the conventional approaches. The AI group had 25 percent and 30 percent more vocabulary and syntax improvement compared to the control group, which obtained only 12 percent and 10 percent. A paired t-test assured the significance of results at $p < 0.05$. Regression analysis identified significant positive relationships between performance and engagement. Qualitative feedback and sentiment analysis also supported the usability and motivational value of the system, confirming the effectiveness and reliability of the AI system for young English learners.

## VI. DISCUSSION AND CONCLUSION

### A. Discussion

The research identifies the potential of an AI-driven personalized learning system to enhance vocabulary and syntax skills in young English learners. With the use of adaptive learning models, NLP-based chatbots, and gamification, the system offers instant feedback and dynamically adapts to the learner's needs [29]. Experimental results indicate a 25 percent improvement in vocabulary recall and a 30 percent improvement in syntax accuracy compared to conventional approaches. Increased levels of engagement and constructive learner feedback underscore the system's power to transform language learning. Against such challenges as access issues, the model promises a viable alternative to clumsy, single-size-fits-all instruction.

### B. Conclusion and Future Works

This study proposes that, against traditional methods, AI-powered personalized learning systems are effective at significantly improving vocabulary retention and syntax acquisition among young English learners. The inclusion of personalized content-specific adaptive learning models, an NLP-based chatbot, and hybrid game-logics provides real-time feedback and maximum engagement, ensuring measurable success in proficiency. The suggested approach provides real-time adaptive feedback, dynamic difficulty management, and gamified interactions specific to young learners—beating current models bound by inflexible vocabulary flow or absence of personalization. Its curriculum-matched yet flexible framework maximizes engagement and learning gain, rendering it better than rigid, one-size-fits-all AI language systems. Nonetheless, the system performance of the AI-based system was best realized in learner settings of high involvement, stable interaction data, and rich response behavior, which implies that the algorithm is best designed to data-intensive, behaviorally engaged learner profiles.

Further studies will deal with enhancing AI-powered language learning systems with better new NLP models that might improve context comprehension and conversational

abilities. Fortunately, other forms of learning can be explored involving multi-modal forms of learning whereby interactions with visual, auditory, and kinesthetic modalities would further support engagement and retention of students. Expanding the study to be focused on different age groups and diverse linguistic backgrounds will provide a broad understanding of the impact of AI for language acquisition. Finally, the development of a model where AI and human beings will collaborate for a blackboard must support teachers, not by replacing them, will be explored in order to develop a more balanced approach to the effectiveness of the learning ecosystem.

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# DenseRSE-ASPPNet: An Enhanced DenseNet169 with Residual Dense Blocks and CE-HSOA-Based Optimization for IoT Botnet Detection

Mohd Abdul Rahim Khan
Department of Electrical Engineering and Computer Science, A'sharqiyah University, IBRA-400 OMAN

***Abstract*—The growing prevalence of Internet of Things (IoT) devices has heightened vulnerabilities to botnet-based cyberattacks, necessitating robust detection mechanisms. This paper proposes DenseRSE-ASPPNet, an advanced deep learning framework for botnet detection, incorporating comprehensive preprocessing, feature extraction, and optimization. The preprocessing pipeline includes data cleaning and Min-Max normalization to ensure high-quality input data. The DenseNet169 backbone is enhanced with Residual Squeeze-and-Excitation (RSE) blocks for channel-wise attention recalibration and Atrous Spatial Pyramid Pooling (ASPP) for capturing multi-scale spatial patterns, enabling effective feature extraction. Hyperparameter optimization is performed using the Cyclone-Enhanced Humboldt Squid Optimization Algorithm (CE-HSOA), which balances global exploration and local exploitation, ensuring faster convergence and enhanced robustness. Experimental results demonstrate the superior performance of the proposed framework, achieving 99.00 per cent accuracy, 96.40 per cent sensitivity, and 99.95 per cent specificity, significantly minimizing false positives and false negatives. The proposed DenseRSE-ASPPNet provides an efficient, scalable, and effective solution for mitigating botnet threats in IoT environments.**

***Keywords*—*Internet of Things; botnet detection; DenseRSE-ASPPNet; residual squeeze-and-excitation blocks; Cyclone-Enhanced Humboldt Squid Optimization Algorithm***

## I. INTRODUCTION

The connectivity of billions of intelligent objects with internet-based communication capabilities is known as the "Internet of Things." The number of commonplace machines that have sensors built in and are able to interact online has significantly increased in recent years. By fusing digital intelligence with physical equipment, the Internet of Things makes the world wiser. There is a lot of data exchange between the connected devices, and security is the main issue with IoT [1], [2], [3]. IoT devices are vulnerable to several types of cyberattacks since they connect objects to the internet and allow them to communicate with one another without human intervention. An ever-growing pool of attack resources is made possible by the quick spread of unsecured IoT devices and the simplicity with which attackers can find them via web services like Shodan. Attackers can now launch extensive attacks, including phishing, spam, and Distributed Denial of Service (DDoS), against Internet resources by assembling and utilizing many of these susceptible IoT devices [4], [5], [6]. At the very beginning of IoT device design and deployment, appropriate security requirements should be determined in order to guarantee the security of the IOT network and devices.

Since the Internet of Things is still in its infancy, it does not yet have a strong security framework or system, which puts sensitive data at risk. To keep IoT entities, businesses, and individuals safe, modern security techniques must be implemented on IoT networks. Botnet-based DDoS attacks, in which hackers infect devices with scripts, pose the biggest security threat to the Internet of Things [7], [8]. Botnet detection is a significant difficulty in the cybersecurity field due to the variety of botnet structures and protocols and the constant development of new, clever methods by attackers to damage networks through botnet-assisted attacks [9], [10]. An intrusion detection system (IDS) is more successful at defending a computer network from external threats, even if many solutions, like firewalls and encryption, are designed to tackle Internet-based cyberattacks. Therefore, identifying and stopping different kinds of harmful network communications and computer device usage is the main objective of an intrusion detection system (IDS) [11], [12], [13]. IDS, monitor and analyses a network's regular everyday activity to detect and identify hostile cyberattacks. Enhancing a system's security requires an intrusion detection system (IDS) that can detect botnets in the network and different botnet-assisted attacks.

The complexity and evolution of botnets have led to the proposal of numerous botnet detection techniques. The use of machine learning (ML) techniques for botnet identification has become increasingly popular within the past ten years. Before ML models are learned or trained, feature extraction is a crucial step. When learning and drawing conclusions, these characteristics act as discriminators. Although some of the current methods for detecting botnets rely on packet information or traffic features, they are rendered ineffective when traffic patterns are encrypted or secret, and traffic patterns can be purposefully changed to evade detection [14], [15]. Further, the inability of flow-based machine learning algorithms to identify botnets to capture the dynamic topological structure of communication networks is one of their main shortcomings.

The proposed approach presents an improved DenseNet169-based deep learning framework enriched with Squeeze-and-Excitation (SE) blocks and Atrous Spatial Pyramid Pooling (ASPP) to address the shortcomings of current botnet detection techniques. This design tackles issues including restricted spatial pattern identification in network

traffic, shallow gradient propagation, and ineffective feature extraction. Whereas, ASPP captures multi-scale spatial data without adding computing overhead, the addition of SE blocks enhances channel-wise attention. Advanced pre-processing methods further guarantee high-quality input data, and the Self-Adaptive Humboldt Squid Optimization Algorithm (HSOA) optimizes the model's performance by fine-tuning the hyperparameters. For the detection of multi-class botnet attacks in IoT systems, this all-encompassing method improves detection accuracy and robustness, making it extremely effective. The following are the paper's main contributions:

Development of an advanced DenseNet169-based deep learning model, DenseSE-ASPPNet, integrating Residual Squeeze-and-Excitation (RSE) blocks for channel-wise attention and Atrous Spatial Pyramid Pooling (ASPP) for multi-scale feature extraction.

Incorporation of the Cyclone-Enhanced Humboldt Squid Optimization Algorithm (CE-HSOA) for efficient hyperparameter tuning, achieving a balance between global exploration and local exploitation.

The Residual Squeeze-and-Excitation (RSE) block is an enhancement to the standard Squeeze-and-Excitation (SE) block, incorporating a residual learning approach to improve feature recalibration, which helps with better channel-wise attention and more robust feature extraction.

The paper is structured as follows: Section II presents a comprehensive literature review on existing botnet detection methods. Section III details the DenseSE-ASPPNet framework. Section IV compares the performance of DenseSE-ASPPNet with other methods. Finally, Section V provides the conclusion.

## II. Literature Review

This section discusses the recent existing papers related to the Botnet attack detection.

In 2022, Nookala Venu, et al., [16] employing machine learning to detect botnet assaults in the Internet of Things. The increasing number of IoT devices that are susceptible to botnet assaults has made them a serious threat to internet security. Many machine learning (ML)-based methods have been released so far to identify different types of botnet attacks. Regardless of the dataset, this study proposes a universal feature set that is extrapolated based on the frequency counting approach and the Logistic Regression method to better detect botnet attacks. There are six main steps in the process overall, starting with data collection and ending with the detection of botnet attacks.

In 2022, Alissa, et al., [17] Detecting botnet attacks in IoT with machine learning. UNSW-NB15, the most comprehensive dataset that is publicly accessible, was used in that study. Exploratory Data Analysis (EDA) is the statistical analysis stage that examines the entire dataset. In the future, the model will be able to be trained on a big dataset. SVM and Random Forest are two examples of machine learning classifiers that can be tested. Runtime Botnet detection can also be done with deep learning models in addition to ResNet50 and LSTM models.

In 2023, Al-Fawa'reh, et al., [18] Detecting malware botnets in IoT networks with deep reinforcement learning. MalBoT-DRL, a powerful malware botnet detector that uses deep reinforcement learning (RL), is presented in this paper. Enhanced generalizability and robustness against model drift are features of MalBoT-DRL, which is designed to detect botnets at every stage of their lifespan. Damped incremental statistics and an attention reward mechanism are combined in this model, which hasn't been thoroughly studied in the literature. The dynamic adaptation of MalBoT-DRL to the constantly evolving malware patterns in IoT environments is made possible by this integration.

In 2022, Kalakoti, et al., [19] Robust feature selection for automated botnet detection in Internet of Things networks using statistical machine learning. In this research, we minimize feature sets for machine learning tasks, which are structured as six distinct binary and multiclass classification problems according to the stages of the botnet life cycle. More precisely, for every classification task, we determined the best feature sets by combining filter and wrapper techniques with particular machine learning techniques. The SFS and SBS wrapper approaches worked well for identifying the best feature sets for each classification.

In 2023, Taher, et al., [20] IIoT botnet detection using a dependable machine learning model. In this paper, we offer a unique feature selection algorithm, FGOA-kNN, to select the most relevant features. It is based on a hybrid filter and wrapper selection strategy. The Grasshopper algorithm (GOA) is used to reduce the features that are ranked highest in the new technique that is combined with clustering. Additionally, a suggested technique called IHHO chooses and modifies the hyperparameters of the neural network to effectively identify botnets. To improve the global search process for ideal solutions, three enhancements are made to the proposed Harris Hawks algorithm.

In 2022, Waqas, et al., [21] Botnet attack detection using machine learning in cloud-based Internet of Things devices. Investigating cyber security in the face of malware, DDOS, and B-IDS attacks is the goal of this research paper. In order to detect botnet attacks, various machine learning algorithms have been used, including support vector machines, naive Bayes, linear regression, artificial neural networks, decision trees, random forests, fuzzy classifiers, K-nearest neighbors, adaptive boosting, gradient boosting, and tree ensembles.

In 2022, Alrayes, et al., [22] a botnet detection model for the IoT environment is designed using the barnacles mating optimizer with machine learning (BND-BMOML). The BND-BMOML model that is being presented is centered on identifying and recognizing botnets in the context of the Internet of Things. To achieve this, the BND-BMOML model first adopts a data standardization strategy. The BMO algorithm is used in the given BND-BMOML model to choose a useful collection of characteristics. An Elman neural network (ENN) model is used in this study's BND-BMOML model for botnet detection. Lastly, to illustrate the work's originality, the proposed BND-BMOML model employs a chicken swarm optimization (CSO) technique for the parameter tuning procedure.

In 2022, Almuqren, et al., [23] botnet detection using hybrid metaheuristics and machine learning in an IoT context supported by the cloud. The Hybrid Metaheuristics with Machine Learning based Botnet Detection (HMMLB-BND) approach is presented in this paper for the Cloud Aided IoT context. In the context of cloud-based IoT, the proposed HMMLB-BND technique focuses on the identification and categorization of botnet attacks. The Modified Firefly Optimization (MFFO) method is used in the HMMLB-BND technique that is being presented for feature selection. For botnet identification, the HMMLB-BND algorithm employs a hybrid convolutional neural network (CNN)-quasi-recurrent neural network (QRNN) module. Using the chaotic butterfly optimization algorithm (CBOA), the best hyperparameter tuning procedure is carried out.

In 2022, Kumar, et al., [24] early IoT botnet detection based on machine learning and network-edge traffic. We introduce EDIMA, a lightweight IoT botnet detection tool that can be placed at home networks' edge gateways that aims to identify botnets before an attack is launched. A unique two-stage Machine Learning (ML)-based detector designed especially for IoT bot identification at the edge gateway is part of EDIMA. In order to identify individual bots, the ML-based bot detector first uses ML algorithms for classifying aggregate traffic, followed by tests based on the Autocorrelation Function (ACF). A policy engine, a feature extractor, a traffic parser, and a malware traffic database are also included in the EDIMA architecture.

In 2023, Catillo, et al., [25] a deep learning technique for IoT botnet detection that is portable and cross-device. Complex machine learning architectures are used in many of the current intrusion detection system (IDS) concepts for the Internet of Things. These architectures typically offer a single model for each device or assault. The size and dynamic nature of contemporary IoT networks make these methods inappropriate. In order to learn a single IDS model rather than numerous distinct models over the traffic of various IoT devices, this study suggests a novel IoT-driven cross-device technique. Since a semi-supervised strategy is more applicable to unforeseen attacks, it is used. The approach is built on an all-in-one deep autoencoder, which uses regular traffic from many IoT devices to train a single deep neural network. Table I compare the existing papers related to the Botnet attack detection.

TABLE I. COMPARISON OF THE LITERATURE REVIEW PAPERS

| Study | Method | Detection Technique | Advantages | Disadvantages |
|---|---|---|---|---|
| Nookala et al. [16] | Logistic Regression | Botnet detection using frequency counting | Simple and efficient method; good for basic botnet detection tasks | May not handle highly complex attacks well due to the simplicity of the frequency counting method. |
| Alissa et al. [17] | SVM, Random Forest, ResNet50, LSTM | Botnet detection in IoT | Effective for large datasets; can utilize deep learning for more complex attack patterns | Requires large datasets for training; computationally intensive for real-time detection. |
| Al-Fawa'reh et al. [18] | Deep Reinforcement Learning (DRL) | Malware botnet detection | Enhanced generalizability and robustness; adapts dynamically to evolving malware patterns | Complexity of DRL models may lead to high computational cost and long training times. |
| Kalakoti et al. [19] | Statistical ML | Botnet detection | Effective for binary and multiclass classification; good for identifying relevant features | The feature selection process can be computationally expensive and may not generalize well across different datasets. |
| Taher et al. [20] | kNN, Harris Hawks Optimization | IIoT botnet detection | Combines hybrid filter and wrapper methods for better feature selection; effective for IIoT | High computational overhead due to the hybrid approach and complexity of the optimization algorithms. |
| Waqas et al. [21] | Various ML Algorithms (SVM, ANN, DT, RF, etc.) | Botnet detection | Offers a variety of classifiers for different attack types; flexible and adaptable | Limited by the effectiveness of individual classifiers in handling diverse types of botnet attacks. |
| Alrayes et al. [22] | Elman Neural Network (ENN) | Botnet detection in IoT | Efficient in IoT environments; uses BMO for effective feature selection | May struggle with real-time detection and the complexity of feature selection using the BMO method. |
| Almuqren et al. [23] | Hybrid CNN-QRNN | Botnet detection in cloud-based IoT | Combines CNN and QRNN for better detection performance in cloud IoT | High computational demand due to the hybrid neural network and feature selection processes. |
| Kumar et al. [24] | ML-based two-stage detector | Early IoT botnet detection at edge | Lightweight and fast detection at edge gateways; helps in early detection | May not be effective against sophisticated botnet attacks with complex behaviors or new attack patterns. |
| Catillo et al. [25] | Deep Autoencoder | Cross-device IoT botnet detection | Uses semi-supervised learning, which is beneficial for handling unforeseen attacks | Challenges in dealing with unforeseen or novel attack types due to the semi-supervised nature of the model. |
| Study | Methodology | Detection Technique | Advantages | Disadvantages |

The increasing number of Internet of Things (IoT) devices has made them a prime target for botnet attacks, presenting a significant challenge for network security. The detection of botnet assaults in IoT environments is critical, yet existing approaches face various limitations in terms of computational efficiency, adaptability to evolving attack patterns, and the ability to handle complex or unforeseen attack types. Many machine learning (ML) and deep learning (DL) techniques have been proposed for botnet detection, utilizing methods like Logistic Regression, SVM, Random Forest, and deep reinforcement learning. However, these methods often struggle with issues such as high computational demands, limited generalizability, and difficulty in real-time detection. Additionally, feature selection and optimization processes, essential for improving detection accuracy, are computationally expensive and may not generalize well across diverse IoT environments.

Thus, there is a need for more efficient and adaptive botnet detection models that can operate effectively in dynamic and resource-constrained IoT environments. These models should be capable of detecting a wide range of attack types, including novel and sophisticated threats, with minimal computation overhead and in real-time. Developing such a model requires addressing the challenges of feature selection, optimization, and ensuring robustness against evolving malware patterns.

## III. Proposed Methodology

The DenseSE-ASPPNet is proposed as the botnet detection system that combines advanced pre-processing, feature extraction, and optimization techniques. Pre-processing begins with the cleaning of data from entries that may be irrelevant or missing; then Min-Max normalization of features into a consistent scale to efficiently train the model is applied. For feature extraction, we use the DenseNet169 backbone, allowing for feature reuse through dense connections for the extraction of compact informative representations. In addition, RSE blocks improve channel-wise attention recalibration, which helps the model to focus more on important features. ASPP is used to capture multi-scale spatial patterns, which are very important for botnet activity detection at different resolutions. Finally, the hyperparameters of the model are optimized using the CE-HSOA, which combines global exploration and local exploitation to ensure faster convergence and enhanced robustness. Together, these modules enable DenseSE-ASPPNet to effectively detect botnet activities in IoT networks. The proposed Botnet attack detection model is shown in Fig. 1.

### A. Pre-processing

Pre-processing in the DenseSE-ASPPNet architecture consists of two key operations: data cleaning and Min-Max normalization. Data cleaning cleans irrelevant, missing, or erroneous entries from the raw network traffic data so that only valid information is utilized. After data cleaning, all features are scaled within a fixed range by applying Min-Max normalization.

*1) Data cleaning:* The main purpose of data cleaning is to remove unusual data from the original data, such as duplicating, missing, or illegal data. When an experiment is repeated, all duplicate data are eliminated and just the data that appears for the first time are retained. The gaps are filled in by averaging the data from the preceding and subsequent hours. This is shown in Eq. (1),

$$x_i = \frac{x_{i-1}+x_{i+1}}{2} \quad (1)$$

In the padding data, $x_i$ represents the data to be filled, $x_{i-1}$ represents the data from the previous hour, and $x_{i+1}$ represents the data from the next hour. Unlawful data in this experiment are those that have a value of 0 but shouldn't be 0. It is also replaced by the average value of the data from the preceding and following hours, which is determined by Eq. (1).

*2) Min- Max normalization:* In information processing, data normalization is a crucial step. This entails standardizing data in order to reduce complexity, remove redundancy, and enhance data quality. Usually, this method entails scaling numerical data to a uniform range of values in order to standardize it and facilitate comparison and analysis. In this investigation, the min-max normalization method was employed.

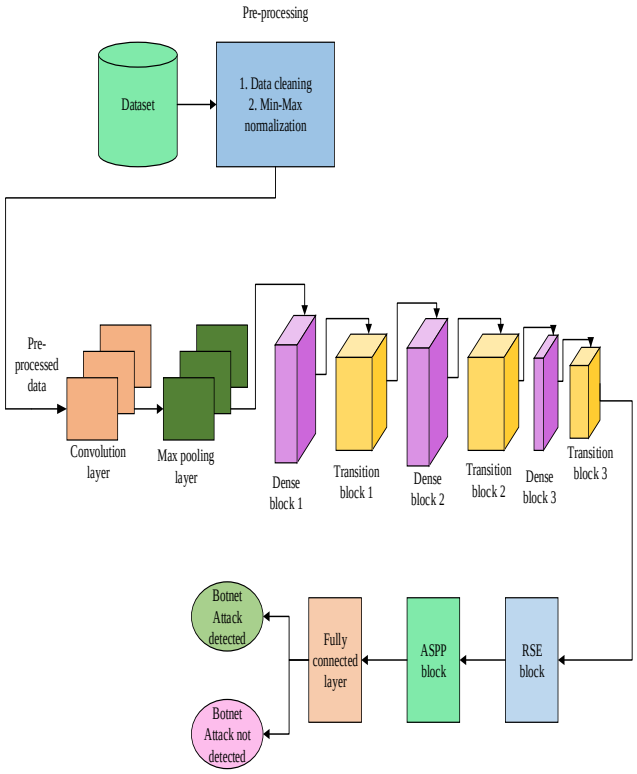


Fig. 1. Block diagram of the proposed Botnet attack detection model.

The initial data is linearly modified using Min-Max normalization. With this method, all scaled data between 0 and 1 is obtained. The following Eq. (2) can be used for this: The relationships between the original data's values are preserved using Min-Max normalization.

$$Z^* = \frac{z-\min(z)}{range(z)} = \frac{z-\min(z)}{max(z)-\min(z)} \quad (2)$$

The minimal value is denoted by min⁡(z), while range (z) denotes the range between maximum and minimum. The breadth of the interval is 1, and the range of Z^* is within the range [0, 1].

### B. DenseRSE-ASPPNet

DenseRSE-ASPPNet is proposed as an effective model for botnet detection using advanced feature extraction techniques. Using the DenseNet169 as the backbone, it explores dense connections that allow feature reuse while learning compact and informative representations for the input data. Furthermore, the RSE blocks enhance feature recalibration capabilities by making the model adaptive to important features while key information is preserved through residual learning. In addition, Atrous Spatial Pyramid Pooling (ASPP) is used to capture multi-scale spatial patterns that are critical for botnet activity detection, which can occur at different spatial resolutions. Combining DenseNet, RSE blocks, and ASPP enables the DenseRSE-ASPPNet model to effectively extract relevant features for accurate and robust botnet detection in IoT networks.

Convolutional layers, max pool layers, transition layers, and dense (fully connected) layers make up the DenseNet. ReLU is used throughout the model's design, whereas SoftMax is used to activate the top layer. The maxpool layers reduce the dimensionality of the input, while the convolutional layers recover the image's characteristics. In the stack, the first flattened layer is followed by the fully linked layers. The flatten layer functions as an artificial neural network and receives a single input array. The DenseRSE-ASPPNet model is shown in Fig. 2.

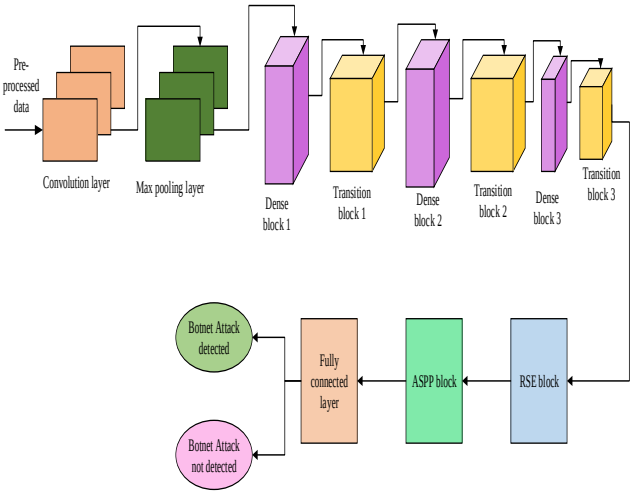


Fig. 2. Architecture of the DenseRSE-ASPPNet model.

*1) Convolution layer:* To put it simply, an activation occurs when a convolutional layer applies a filter to an input. Continuous application of the filter to an input result in a feature map that shows the intensity of the detected features at different locations within the input. ReLU and other activation methods can then be applied to a feature map that has been created using several filters. Often, the operation between these two entities is a dot product since the filter employed in a convolutional layer is narrower than the input data. Assuming a P×P square neuron element, the outcome of this layer would be (P-m+1)×(P-m+1), followed by a filter of size m×m. The nonlinear input to the unit $x_{ij}^{l}$ is determined by summing the inputs from the layer cells preceding them, as per Eq. (3).

$$x_{ij}^{l} = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \mu_{ab} y_{(i+a)(j+b)}^{l-1} \tag{3}$$

The convolutional layer's implementation of the identified non-linearity is demonstrated by Eq. (4).

$$y_{ij}^{l} = \lambda(x_{ij}^{l}) \tag{4}$$

*2) MaxPool layer:* Adding a maxpool layer to a CNN is primarily done to reduce the dimensionality of the feature map. The maxpool layer summarizes the features in the region that the pooling layer has filtered, applying a filter on the feature map similarly to the preceding layer. n_h×n_w×n_c, which represent the feature map's height, width, and channels, respectively, are presumed to be present in a feature map. The feature map's dimensions are determined by Eq. (5) when the maximum pooling ( 〖max〗 _p) across the size f and stride s filters is utilized.

$$max_p = \frac{(n_h - f + 1)}{s} \times \frac{(n_w - f + 1)}{s} \times n_c \tag{5}$$

*3) Dense layer:* The fully connected layer is where the majority of classification at the network's end occurs. Unlike pooling and convolution, it is a global procedure. A global analysis is performed on the output of all the preceding layers using the information gathered from the feature extraction steps. By doing this, it creates a non-linear blend of the characteristics that are utilized to classify information. The communication between all neurons in a thick layer and all neurons in the layer above it is referred to as strongly coupling in a neural network. A matrix-vector multiplication occurs whenever each neuron in this layer sends information to its matching neuron in the layer underneath. The formula for matrix-vector multiplication is provided in Eq. (6).

$$M.\lambda = \begin{matrix} m_{11} & m_{12} & \cdots & m_{1y} & p_1 \\ m_{21} & m_{22} & \cdots & m_{2y} & p_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{x1} & m_{x2} & \cdots & m_{xy} & p_y \end{matrix} \tag{6}$$

A matrix with dimensions of × y and 1× y, respectively, is represented by the variables M and p in the equation above. Backpropagation can be used to update the previous layer's parameters, which comprise the variable matrix, during training. To backpropagate over the learning rate, which is defined by changing the weights for the layer ly designated by ω^ly and bias represented by the variable B^ly of the neural network, utilize Eq. (7) and Eq. (8) respectively.

$$\omega^{ly} = \omega^{ly} - \alpha \times d\omega^{ly} \tag{7}$$

$$B^{ly} = B^{ly} - \alpha \times dB^{ly} \tag{8}$$

The dω and db are calculated using a chain rule (from the output layer via the hidden layers to the input layer). These are dω and db, which are the partial derivatives of ω and b of the loss function. Eq. (9) through Eq. (12) are utilized to calculate dω and db.

$$d\omega^{ly} = \frac{\partial L}{\partial \omega^{ly}} = \frac{1}{n} dZ^{ly} A^{[ly-1]T} \quad (9)$$

$$\mathrm{dB^{ly}} = \frac{\partial \mathrm{L}}{\partial \mathrm{B^{ly}}} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{dZ^{ly(i)}} \quad (10)$$

$$\mathrm{dA^{ly-1}} = \frac{\partial \mathrm{L}}{\partial \mathrm{A^{[ly-1]}}} = \mathrm{W^{lyT}} \mathrm{dZ^{ly}} \quad (11)$$

$$\mathrm{dZ^{ly}} = \mathrm{dA^{ly}} \times \mathrm{g'(Z^{ly})} \quad (12)$$

As per the previously mentioned equations, the layer ly linear activation is represented by the variable Z^ly, and the differential of the Z^ly-related non-linear function is denoted by g^' (Z^ly). The symbol for the nonlinear activation function at the same layer is A^ly.

*4) Transition layer:* A CNN uses a transition layer to make the model simpler. Usually, a transition layer uses an 11-layer convolution to lower the number of channels and a stride 2 filter to cut the input's height and breadth in half.

*5) SE block with residual connection:* The SE Block is utilized in this situation due to its simplicity in integrating into any model and its capacity to rectify information loss by recalibrating features with a negligible increase in parameters. By passing the input features via the GAP, the SE-Block-based attention module condenses each channel into a single feature, or scalar value. The two phases of the SE Block are excitation and squeezing. Every channel in the image is made one-dimensional during the squeeze stage by using global average pooling, or GAP. A rectified linear unit (ReLU) and a sigmoid are two completely connected layers that the squeezed vector passes through during the recalibration stage. In order to highlight the key information, the flattened vector is then multiplied by the image that has undergone a 1 × 1 convolution and the weight, which represents squeezed information. An SE Block is depicted in Fig. 3. The SE Block's reduction ratio is a hyperparameter that modifies the number of nodes in the ReLU and fully linked layer. The number of parameters rose as the reduction ratio dropped. The number of parameters dropped as the reduction ratio grew. In other words, it is a hyperparameter associated with variations in computing cost and capacity. The recalibrated output and the input layer are connected by a residual connection that is introduced at the recalibration stage. A direct shortcut between a module's input and output is another design element in the residual connection block that improves the gradient flow during backpropagation while maintaining information. Adding the recalibrated feature map back to the input is how a SE Block that uses residual connections is implemented.

The SE channel attention process involves several important equations. The Squeeze operation uses global average pooling to reduce the input feature map (H×W×C) to 1×1 ×C. The height, breadth, and number of channels of the original feature map are denoted by H, W, and C, respectively. This could be shown in Eq. (13),

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i,j) \quad (13)$$

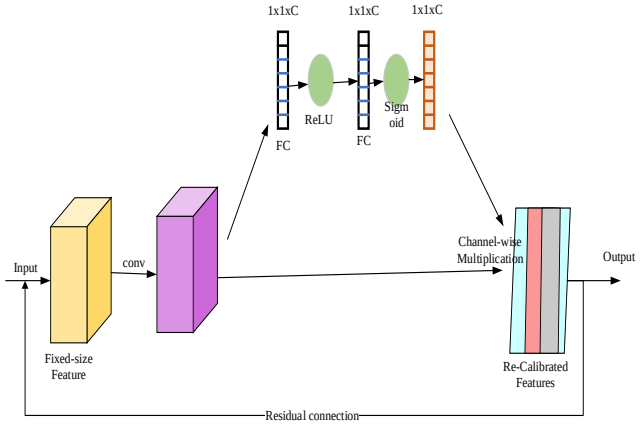


Fig. 3. Block diagram of the RSE block.

In this case, u_c is the feature value of the c^th channel at position (i,j) in the input feature map, and z_c is the Squeeze output of the c^th channel. An activating mechanism and two fully connected layers are used in the Excitation phase to establish channel weights and understand the correlations between channels. In Eq. (14),

$$\mathrm{s} = \sigma(\mathrm{W_2}\delta(\mathrm{W_1 z})) \quad (14)$$

where, z is the Squeeze phase's output, δ is the ReLU value, σ is the Sigmoid function, s is the generated channel weight vector, and $W_1$ and $W_2$ are learned weight parameters. Furthermore, after the SE attention system is executed, the feature specification is obtained by multiplying the channel's weights by the initial features. In Eq. (15), the recalibration procedure is displayed.

$$y_c = s_c . u_c \quad (15)$$

The input features (u_c) are appended to the recalibrated features (y_c) in order to create a residual connection:

$$\hat{y}_c = \mathrm{y_c} + \mathrm{u_c} \quad (16)$$

This equation can also be written as:

$$\hat{y}_c = (s_c . u_c) + u_c \quad (17)$$

The addition ensures that the recalibrated features enhance the input features without overwriting the original information, maintaining a balance between recalibration and preservation.

*6) ASPP module:* The ASPP module's dilated convolution, sometimes referred to as extended convolution or atrous convolution, is distinguished by the addition of gaps between the convolution kernel's constituent pieces. This preserves the original input feature map's height and width while expanding the kernel's receptive field. The convolution kernel's spacing is indicated by the dilation rate. By altering the dilation rate, the filter's receptive field can be adjusted appropriately. Every two convolutional kernel elements are separated by (r-1) zeros, as seen in Fig. 3. k ' = k + (k - 1) × (r - 1) is the kernel's effective

size. Among these, r stands for the dilation rate and k for the convolutional kernel's size. Dilated convolution is the same as ordinary convolution when r=1. It can modify the convolutional kernel's receptive field by varying the dilation rate without requiring additional calculations or parameters. The basic dilation model is shown in Fig. 4.


Fig. 4. 3×3 Filter with different dilation rate as 1, 2, and 3.

An ASPP module is added at the network's bottom to extract multi-scale features that will aid the network in comprehending and capturing data at various scales. Spatial Pyramid Pooling (SPP) is the foundation of the enhanced ASPP module. The use of dilated convolutions in place of ordinary convolutions is where ASPP and SPP diverge. This module uses dilated convolutions with varying dilation rates as the final prediction in order to merge multiple receptive field features. The ASPP module makes use of adaptive average pooling in conjunction with four parallel dilated convolutions (with dilation rates of 1, 6, 12, and 18), as illustrated in Fig. 5. Batch normalization (BN), ReLU activation, and a convolution operation make up each dilated convolution. Concat can be used to join parallel networks. To guarantee that the output image size stays the same as the input image size, use BN, ReLU, and ordinary convolution (with a kernel size of 1×1).

*7) Fully Connected (FC) layer:* The FC layer performs feature aggregation by combining the learned features from different areas of the input image. The network can provide more sophisticated representations by capturing higher-level patterns and correlations between features thanks to this aggregation. In this assignment, the burst assembly is carried out, and the output of the completely linked layer is frequently used to generate final predictions. The proposed model's final layer has two layers, provides the final output for prediction.

*8) SoftMax activation layer:* Deep learning systems commonly use the softmax activation function to address classification issues. In Eq. (18), where, weight is represented by the variable ω and bias by the variable b over an input vector x, defines the general form of a nonlinear activation function.

$$y = f(\omega \times x + b) \tag{18}$$

The output layer of a convolutional neural network employs the softmax function to estimate the likelihood of each output class. According to the softmax function's specifications, each neuron in the output layer receives a single value. Each of these neurons in the output layer determines the likelihood (or probability) that a certain node will reach the output. When applied to the input, the softmax function is defined over the softmax function Θ. According to Eq. (19), v_i relates to the exponential function of the input vector, represented by e^(v_i ), and the exponent function of the output vector, represented by e^(v_o ), with m instances.

$$\Theta(z)_x = \frac{e^{v_i}}{\sum_{y=1}^{m} e^{v_o}} \tag{19}$$

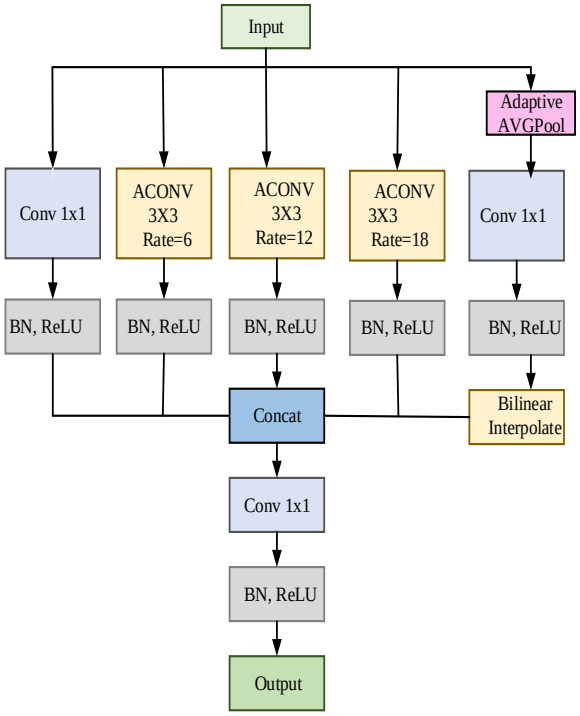


Fig. 5. Structure of the ASPP model.

This work uses softmax as the activation function and the binary cross-entropy loss function as the loss function. Binary cross-entropy has been used in the past to solve binarization challenges. Eq. (20) and Eq. (21) display the binary cross-entropy loss function for a network with n layers.

$$K(\omega, b) = \frac{1}{n}\sum_{i=1}^{n} L(a^{(i)}, a^{(i)}) \tag{20}$$

$$L(\hat{a}, a) = -(a \times \log \hat{a} + (1 - a) \times \log(1 - \hat{a})) \tag{21}$$

With the variable a representing output class 1 and (1-a) representing output class 0, aˆ represents the probability of output class 1 and (1-aˆ) for the class 0 result. The heatmap for the extracted features is shown in Fig. 6.

### *C. Hyper Parameter Tuning of DenseRSE-ASPPNet using CE-HSOA*

Hyperparameter tuning is an important step while optimizing the performance of the model DenseRSE-ASPPNet. The effectiveness of deep learning models, such as DenseRSE-ASPPNet, may be highly reliant on hyperparameters like a learning rate, batch size, number of layers, etc. To effectively find a good combination of hyperparameters, we apply the CE-HSOA.

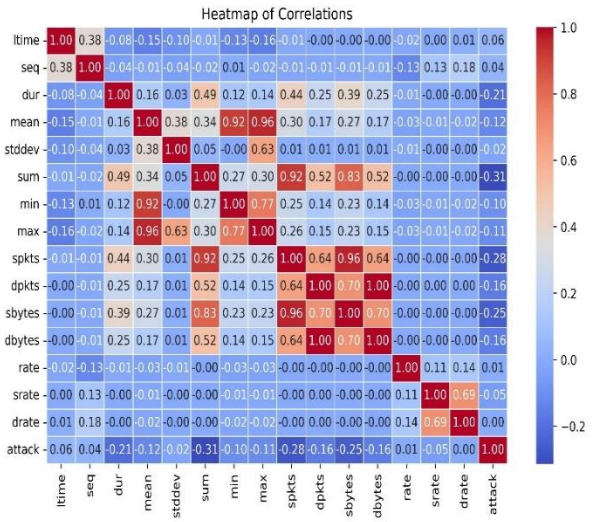


Fig. 6. Heatmap of correlations.

In HSOA, hunting, migration, and mating were important phases. For the search operation, five mechanisms are specified in order to quantitatively model this process. Attacking schools of fish, escaping fish, successfully attacking, attacking smaller squids, and mating Humboldt squids are the components of these methods. As CE-HSOA iterations increase, the search process shifts from exploration to exploitation through mating, bigger squids attacking smaller squids, and fish schools attacking. Fish Escape, however, manages exploration in each iteration.

*1) Generating initial population:* The CE-HSOA population is made up of fish swarms and Humboldt squid. Algorithm 1 is the pseudocode that CE-HSOA employs to create the first population. As may be observed, Humboldt squid are thought to be the best individuals in the population, whereas fish make up the remainder. Since the Hublot squid is larger and more fit than school fish, this problem is in line with nature.

*2) Attack of fish schools:* In CE-HSOA, the attack of fish schools is simulated using Eq. (22).

$$XS^{d}_{new,i} = X_b + V_{jet}.(-XF^{d}_{new,r_1} - PopAll^{d}_{r_2}) \quad (22)$$

According to Eq. (1), $PopAll^{d}_{r_2}$ is the saved $r_2^{th}$ position in the CE-HSOA memory, $XF^{d}_{new,r_1}$ is the position of $r_1^{th}$ fish in $d^{th}$ dimension, $V_{jet}$ is the locomotion velocity parameter, and $XS^{d}_{new,i}$, i is the new position of $i^{th}$ Humboldt squid in $d^{th}$ dimension. Additionally, $r_1$ and $r_2$ are random integer numbers between 1 and the size of the PopAll and the population size of fish, respectively. Responsibility for $V_{jet}$.

*3) Successful attack:* The new position for Humboldt squid ($XS_i$) replaces the existing position for Humboldt squid after the new positions for fish and squid have been updated.

$$XS^{d}_{i} = \begin{cases} XS_i = XS_{new,i}, & if\ FS_{new,i} < FS_i \\ Successful\ escape, & Otherwise \end{cases} \quad (23)$$

The new and current fitness functions of the $i^{th}$ Humboldt squid are denoted by $FS_{new,i}$ and $FS_i$ in Eq. (23).

*4) Successful escape:* When the school of fish is attacked by the squid, the fish flee to a randomly chosen spot. The following equation is used in this escape to update the fish's position and velocity.

$$XF_{new,i} = \begin{cases} XF_i + \overrightarrow{rn}.(P_{best} - XF_i).wf, & if\ nfes < 0.1max_{nfes} \\ XS_i + \overrightarrow{rn}.(ArchiveX_{r_1} - PopAll_{r_2}), & Otherwise \end{cases} \quad (24)$$

The number of function evaluations in Eq. (24) is represented by $nfes$, the maximum number is represented by $max_{nfes}$, $ArchiveX_{r_1}$ is the $r^{th}$ place in the archive of the best results, $XS_i$ is the $i^{th}$ location of the Humboldt squid, $\overrightarrow{rn}$ is the normal random vector, $wf = Fb$, $XF_{new,i}$ is the new position of $i^{th}$ fish, $XF_i$ is the current position of $i^{th}$ fish, and $P_{best}$ is N top of the best positions. The fitness function of $i^{th}$ fish is $F_{f_i}$, while $F_b$ is the best fitness function. If the function evaluation counter is in the first generation of this equation, the fish will migrate toward one of the N best solutions. If not, it shifts to a random location.

*5) Attack of stronger squids to smallest squids:* Fish and Humboldt squid are presumed to be out of the hunt if they are unable to locate a better position in the preceding steps. Thus, the larger Humboldt squid consumes the smaller ones. At this point, the following equation is used to determine the Humboldt squid's location:

$$XS^{d}_{new,i} = XS^{d}_{new,i} + V_{jet_2}.(XS^{d}_{new,i} - X^{d}_{b}) \quad (25)$$

The second velocity parameter in Eq. (25) is $V_{jet_2}$. Based on this connection, it is assumed that the smaller Humboldt squid is in the best position ($X^{d}_{b}$) and that the larger one goes toward it in order to search for the optimum solutions.

*6) Humboldt Squid mating:* In CE-HSOA, the egg position is generated using Eq. (26). It was previously used to improve the deferential evolutionary (DE) method.

$$Eggs = \big(\omega.XS + (1-\omega.P_{best})\big).\gamma + (1-\gamma).pop(r_1,:) + W.(pop(r_3,:) - popAll(r_2,:)) \quad (26)$$

The Humboldt squid egg mass is represented by the variable Eggs in Eq. (27), while the adaptive weights $\omega, \gamma, and\ W$ govern the search procedure. Between 0 and 1 are $\omega\ and\ \gamma$. This equation can be used to estimate $W$:

$$\mathrm{W} = \max\{\omega.\gamma, (1-\omega).\gamma, 1-\gamma\} \quad (27)$$

The current study defines the following equations [Eq. (28) and Eq. (29)] for estimating $\omega\ and\ \gamma$:

$$\omega = \mu_\omega + c_1.x \quad (28)$$

$$\gamma = \mu_\gamma + c_2.\overrightarrow{rn} \quad (29)$$

where, the user determines the constant parameters $c_1$ and $c_2$. Additionally, in the first generation, $\mu_\omega$ and $\mu_\gamma$ are vectors with a value of 0.5, and they are updated in subsequent generations in the manner described below:

$$\mu_{\omega} = \frac{[Diff_F(I).\omega(I)^2]}{[Diff_F(I)].[\omega(I)]} \quad (30)$$

$$\mu_{\gamma} = \frac{[Diff_F(I).\gamma(I)^2]}{[Diff_F(I)].[\gamma(I)]} \quad (31)$$

where, $Diff_F$ is the difference between the fitness of Humboldt squids and their eggs, and I is the index indicating which Humboldt squids are more fit than their eggs in Eq. (30) and Eq. (31). The mating motion in the CE-HSOA is performed multiple times because Humboldt squids mate multiple times during their lifetimes, at each generation. Keep in mind that the γ ought to be higher than zero. Therefore, the following equation is used to rectify the γ value if it falls below zero:

$$\gamma = \mu_{\gamma} + 0.1.\tan(\pi.\mathrm{rnd}) \quad (32)$$

The typical random number rnd in Eq. (32) falls between 0 and 1. The value of x is calculated using Eq. (33):

$$x = \frac{nfes}{max_{nfes}}.\overrightarrow{rnd}^{r.10} \quad (33)$$

In Eq. (33), the normal random vector over right around and the normal random number r are both between 0 and 1, respectively.

*7) Control search process with cyclone foraging:* There are several parameters that influence the CE-HSOA search process, such as $V_{jet}$, $V_{jet_2}$, $x, w_f, W, \omega, and\ \gamma$. To replicate Humboldt squids' shape of locomotion, $V_{jet}$ and $V_{jet_2}$ are used. This is accomplished by using a polynomial function. The third and fourth degrees, respectively, are assigned to the power of this polynomial function for $V_{jet}$ and $V_{jet_2}$. To calculate $V_{jet}$ and $V_{jet_2}$, the following formulas are used.

Incorporating the Cyclone Foraging phase from the Manta Ray Optimization algorithm significantly enhances the CE-HSOA's search process. The movement pattern provided in this phase is that of a spiral, thereby increasing the efficiency of exploring space while also decreasing the chances of falling into a local optimum. This strikes a balance between global exploration and local exploitation, ensuring that it is focused on the promising regions for better refinement of the solution. Moreover, due to its adaptive and dynamic nature, this mechanism accelerates convergence and enhances the algorithm's robustness against premature stagnation. Further improvement of versatility is achieved through incorporation of stochastic movements, thereby making CE-HSOA more effective in solving complex, nonlinear, or multimodal optimization problems.

$$V_{jet} = X_{best} + r.(X_{best} - X_i) + \beta.(X_{best} - X_i) \quad (34)$$

$$V_{jet_2} = (X - a_1).(X - a_2).(X - a_3).(X - a_4) \quad (35)$$

where, $X_{best}$ is the best solution, and $\beta$ is the weight factor. The value of $\beta$ is given by,

$$\beta = 2e^{r\frac{T-t+1}{T}}.\sin(2\pi r) \quad (36)$$

The parameters $a_1$, $a_2$, $a_3$, and $a_4$ of the polynomial function that define its shape are found in Eq. (34) and Eq. (35) and can be used to derive $X$:

$$X = \frac{nfes}{max_{nfes}} \quad (37)$$

where, $w_f$ adjusts the fish's escape radius based on the ratio of the fish's current objective function value to the value of the best objective function. The extent of fish escapement is limited by this parameter during the start of the search, when there are many possible options. However, this parameter approaches one and its effect is mitigated as the number of generations increases. In Eq. (25), the impacts of $XS$ are greater than those of $p_{best}$ because raising the generations in equation 8 raises the value of $x$. The local optima trap is avoided by CE-HSOA with the aid of these factors. In the mating portion, $w_f$, $\omega$ and $\gamma$ oversee preventing the ensuing responses becoming convergent too soon. These settings alter the search range and strike a balance between exploration and exploitation based on the objective function's value and the number of generations.

## IV. Results and Discussions

This section compares the performances of several classification techniques—Proposed Model, CNN, KNN, SVM, and Logistic Regression—across various metrics such as accuracy, sensitivity, specificity, precision, F-measure, NPV, FPR, FNR, and MCC. From the obtained results, the Proposed Model is seen to be performing better than the other techniques across most of these metrics, signifying superior classification performance.

### A. Dataset Description

The N-BaIoT Dataset includes traffic information from nine industrial IoT devices. Of them, seven devices gathered data for eleven classes, while the other two devices gathered data for six classes. The information includes both benign traffic and a range of malicious assaults, including SYN, TCP, UDP, and scan. Within the current version of the dataset, there are 89 csv files totaling 7.58 GB in size, with 1486418 examples of both normal and attack cases. The ten attack and non-attack classifications into which the two botnet attacks, MIRAI and BASHLITE, were divided. These attacks fall into three categories: 1) scan instructions, which are used to identify susceptible IoT devices; 2) ACK, SYN, UDP, and TCP floods; and 3) combo or combination assaults, which are used to establish a connection and send spam to it [26].

### B. Overall Comparison of the Proposed Botnet Attack Detection Model

The Table II compares the performance metrics of the Proposed Model, CNN, KNN, SVM, and Logistic Regression, highlighting the superiority of the Proposed Model across all evaluated criteria.

TABLE II. COMPARISON OF THE PERFORMANCE METRICS

| Techniques | Sensitivity | Specificity | Accuracy | Precision | F-Measure | NPV | FPR | FNR | MCC |
|---|---|---|---|---|---|---|---|---|---|
| **Proposed** | 0.9640 | 0.9995 | 0.9900 | 0.9878 | 0.9842 | 0.9964 | 0.0188 | 0.0548 | 0.9726 |
| **CNN** | 0.9377 | 0.9940 | 0.9744 | 0.9825 | 0.9856 | 0.9934 | 0.0283 | 0.1301 | 0.9608 |
| **KNN** | 0.9280 | 0.9861 | 0.9600 | 0.9767 | 0.9798 | 0.9901 | 0.0749 | 0.1550 | 0.8839 |
| **SVM** | 0.9054 | 0.9789 | 0.9484 | 0.9695 | 0.9755 | 0.9800 | 0.0777 | 0.1432 | 0.8760 |
| **Logistic Regression** | 0.8299 | 0.9344 | 0.9219 | 0.8980 | 0.8976 | 0.9769 | 0.0637 | 0.2172 | 0.8092 |

The Proposed Model shows the highest sensitivity, specificity, accuracy, precision, F-measure, NPV, and MCC at 0.9640, 0.9995, 0.9900, 0.9878, 0.9842, 0.9964, and 0.9726, respectively, and lowest FPR and FNR values of 0.0188 and 0.0548, respectively, indicating effective minimization of false classifications. CNN is the second-best performer with high sensitivity of 0.9377, specificity of 0.9940, and accuracy of 0.9744, but higher error rates than the Proposed Model. KNN shows average performance, with acceptable sensitivity (0.9280) and specificity (0.9861), but high FPR (0.0749) and FNR (0.1550). SVM further drops the sensitivity at 0.9054 and specifically at 0.9789, along with a decreased MCC at 0.8760. The Logistic Regression performs the worst, at the lowest sensitivity (0.8299), specificity (0.9344), and MCC (0.8092), and the highest FPR (0.0637) and FNR (0.2172). In general, the Proposed Model significantly outperforms the other alternatives, demonstrating its strength and effectiveness in classification tasks.

### C. Accuracy, Sensitivity and Specificity

The Table II shows a comparative performance of accuracy, sensitivity, and specificity for different classification techniques. The Proposed Model achieves the highest accuracy (0.9900), signifying its superior ability to classify cases correctly, both positive and negative. CNN follows with high accuracy at 0.9744, while KNN, SVM, and Logistic Regression follow with progressively lower accuracies of 0.9600, 0.9484, and 0.9219, respectively.

Sensitivity, measuring the model to correctly identify positive cases is also highest for the Proposed Model (0.9640), as it signifies the efficiency in minimizing the false negatives. On the other hand, CNN indicates a competitive sensitivity of (0.9377), while KNN indicates somewhat lower at 0.9280; whereas SVM, and Logistic Regression indicate extremely poor sensitivity in detecting positive cases at 0.9054 and 0.8299, respectively. Specificity, which measures the accuracy in detection of negative cases, approaches near perfection for the Proposed Model (0.9995), thus reflecting an excellent ability to reduce false positives. CNN (0.9940) and KNN (0.9861) are also highly specific, while SVM (0.9789) and Logistic Regression (0.9344) performed much weaker. Fig. 7 shows accuracy, sensitivity and specificity values.

### D. Precision and F-Measure

The Table II also reports Precision and F-Measure, two important metrics that reflect the performance of a model in handling positive classifications. Precision measures the proportion of correctly identified positive cases out of all predicted positives, which is a measure of the ability of the model to minimize false positives. The Proposed Model has the highest precision at 0.9878, which means it can very well classify true positives while keeping false positives at bay. The accuracy of CNN is 0.9825, whereas, KNN follows with 0.9767 and then comes SVM with 0.9695, and then Logistic Regression shows the least accuracy with 0.8980. The F-Measure is the harmonic means of precision and sensitivity. It offers a comprehensive view of the performance of the model in correctly identifying positive cases by weighing the trade-off between these two measures. The Proposed Model has the best F-Measure of 0.9842, which indicates its excellent balance between high precision and sensitivity. CNN is also performing well with an F-Measure of 0.9856, which is slightly higher than its precision due to its strong sensitivity. KNN and SVM have moderate F-Measure values at 0.9798 and 0.9755, respectively, while Logistic Regression lags far behind at 0.8976. Precision and F-Measure values are shown in Fig. 8.

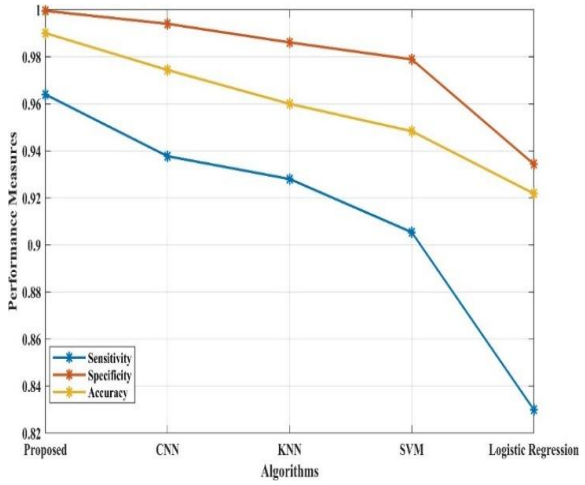


Fig. 7. Comparison of the accuracy, sensitivity and specificity values.

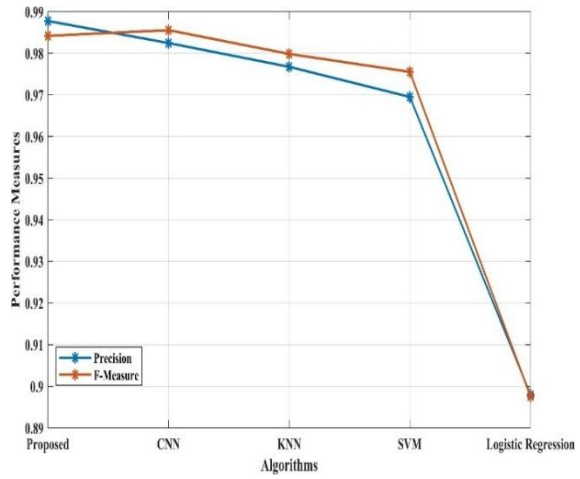


Fig. 8. Comparison of the precision and F-Measure values.

### E. NPV and MCC

The Table II also shows Negative Predictive Value (NPV) and Matthews Correlation Coefficient (MCC), furthering the interpretation of the model's performance. NPV is defined as the proportion of true negatives in all predicted negatives, thus representing how well the model can predict negative cases with minimal false negatives. The Proposed Model attains the highest NPV (0.9964), indicating its high reliability in terms of true negatives. CNN is followed by a strong NPV of 0.9934, followed by KNN at 0.9901, SVM at 0.9800, and Logistic Regression at 0.9769, which means that the performance is declining, and Logistic Regression has the worst ability to classify negative cases. MCC is a comprehensive metric which calculates the correlation between the true and predicted values with all possible outcomes: true positives, true negatives, false positives, and false negatives. The Proposed Model has the highest MCC of 0.9726, which means the model is well-balanced and robust in its prediction. CNN has a high MCC of 0.9608, while KNN and SVM have moderate correlation values at 0.8839 and 0.8760, respectively. Logistic Regression with the lowest MCC is at 0.8092, which reflects the weakest overall predictive power. The NPV and MCC values are shown in Fig. 9.

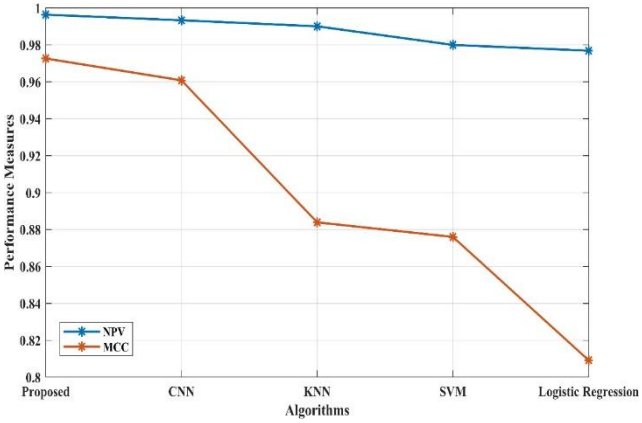


Fig. 9. Comparison of the NPV and MCC values.

### F. FPR and FNR

The Table II evaluates False Positive Rate (FPR) and False Negative Rate (FNR), which evaluate the model's error rates in specific contexts. FPR is the proportion of the false positives to all true negatives, indicating the capacity of the model to get negative cases wrongly classified as positives. The Proposed Model acquired the lowest FPR, which is 0.0188, thereby demonstrating their outstanding capability to minimize false positive and correctly classify negative instances. CNN (0.0283) has an FPR that is slightly above KNN (0.0749), SVM (0.0777), and Logistic Regression (0.0637). Though logistic regression does better than both KNN and SVM in its FPR, it significantly lags behind the proposed model and CNN.

Finally, FNR represents how many of the actual positives in the set were not discovered as positives by the model-thus representing the model's rate of missing true positive occurrences. The Proposed Model has the lowest FNR of 0.0548, indicating its higher efficiency in terms of identifying the right cases with fewer misses. CNN comes next with an FNR of 0.1301, while KNN has an FNR of 0.1550, SVM 0.1432, and Logistic Regression 0.2172, showing higher rates and a greater possibility of missing true positives. FPR and FNR values are compared in Fig. 10.

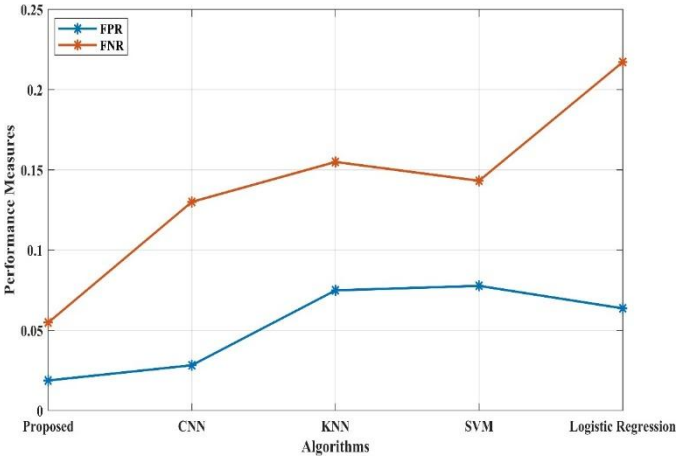


Fig. 10. Comparison of the FPR and FNR values.

## V. Conclusion

In conclusion, the DenseRSE-ASPPNet model gives the best and most efficient approach to botnet detection in IoT networks, surpassing other traditional machine learning techniques. Through the use of advanced methods such as the DenseNet169 backbone, RSE blocks, and ASPP, it can efficiently extract informative features and capture multi-scale spatial patterns. Optimized for hyperparameters of the model, applying the CE-HSOA, which boosts the results to have more robust and faster convergence. Therefore, a model that yields better Metrics and shows a high percentage of correctness for identifying bot activities while having very less errors involving false positives and false negatives.

The performance comparison highlights the advantages of DenseRSE-ASPPNet over other models such as CNN, KNN, SVM, and Logistic Regression. The proposed model achieves the highest Accuracy (0.9900) and Sensitivity (0.9640), demonstrating its strong ability to correctly identify botnet traffic. Its Specificity (0.9995) and Precision (0.9878) further showcase its reliability in minimizing false positives while maintaining high detection performance. In contrast, models like CNN and SVM show lower performance, particularly in terms of FNR, with SVM having an FNR of 0.1432. KNN also struggles with a higher False Positive Rate (FPR) of 0.0749, indicating that it is less effective in distinguishing botnet traffic. Logistic Regression exhibits the lowest performance across most metrics, especially in Sensitivity and Accuracy, underscoring its limitations for complex tasks like botnet detection. Overall, the results demonstrate that DenseRSE-ASPPNet provides a significant improvement in botnet detection performance, making it a highly effective solution for securing IoT networks.

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# Clustering Analysis of Physicians' Performance Evaluation: A Comparison of Feature Selection Strategies to Support Medical Decision-Making

Amani Mustafa Ghazzawi[1*], Alaa Omran Almagrabi[2], Hanaa Mohammed Namankani[3]
Department of Information Systems-Faculty of Computing and Information Technology,
King Abdulaziz University, Jeddah., Saudi Arabia[1]
Department of Management Information Systems-Faculty of Business Administration, Taif University, Taif, Saudi Arabia[1]
Department of Information Systems-Faculty of Computing and Information Technology,
King Abdulaziz University, Jeddah, Saudi Arabia[2]
Department of Information Systems-Faculty of Computing and Information Technology,
King Abdulaziz University, Jeddah, Saudi Arabia[3]

***Abstract*—Evaluating physicians' performance is one of the fundamental pillars of improving the quality of healthcare in medical institutions, as it contributes to measuring their ability to provide appropriate treatment, interact effectively with patients, and work within healthcare teams. This study aims to explore the impact of attribute selection on the accuracy of physician clustering using the K-Means algorithm, to improve physician performance assessment. Three datasets containing professional, medical, and administrative attributes were analyzed, such as age, nationality, job title, years of experience, number of operations, and evaluations from various entities. The optimal number of clusters was determined using the Elbow and Silhouette Score methods. The results showed that the original feature set and Lasso features performed best at k = 3, with a clear distinction between clusters. The "three-star" cluster performed well at k = 2 but lost some fine details. It was also shown that attribute selection directly affects the number and accuracy of clusters resulting from clustering, allowing for a clearer classification of physician categories. The study recommends using either original features or Lasso features to achieve more effective clustering, which supports improved recruitment, training, and management decision-making processes in healthcare organizations.**

***Keywords*—Physicians; performance; evaluation; clustering; k-means; features; decision making**

## I. INTRODUCTION

Physician performance evaluation is essential for improving the quality of healthcare and ensuring the provision of effective and safe medical services. With the advancement of data analysis techniques, it has become possible to use modern methods, such as clustering, to group physicians based on objective criteria based on professional performance, multiple evaluations, and practical experience. The effectiveness of these methods depends largely on the selection of appropriate attributes that help identify differences between different categories of physicians. Several studies have been conducted on physician performance evaluation. Brennan et al. found that most studies in the healthcare sector relied on manual assessment of physician performance through direct management, encompassing both professional and personal aspects. In their traditional approach, he and Baker used attributes such as physician personal information (age, speciality, gender), medical knowledge, communication skills, peer evaluation, patient satisfaction, and practical experience [1]. Kuemerle demonstrated that these methods, despite their high cost, are comprehensive and effective [2]. Zhang's study relied on several tools, including regression analysis, integrating Norman's theory of action and Reson's theory of human error, as well as developing a medical practice framework, a MOC program, systematic searches of electronic databases, a discretionary survey system, Pearson's correlation coefficient, and linear mixed models [3]. In contrast, another study used artificial intelligence to evaluate physician performance. Shi et al. relied on online text consultations between physicians and patients, using Python programming and a simple partitioning ordinal mapping (SVMOP). Model features included the number of medical terms used by the physician, the number of patient questions, as well as predictive features such as tact and emotional words [4].

With the advancement of data analysis technology, it has become possible to use advanced methods such as clustering to identify hidden patterns within complex data sets. Clustering, according to Xu & Wunsch, is a data analysis technique that relies on dividing data into homogeneous groups, each with similar characteristics [5]. This method can be applied to physician data to extract the most influential attributes in evaluating their performance, thereby improving evaluation quality. The importance of this study lies in exploring the extent to which clustering contributes to improving the accuracy of predictive models for evaluating physician performance. In a study conducted by Ghazzawi et al., different datasets collected from an Egyptian hospital were compared. They sought to identify the attributes that best represent physician performance evaluation criteria using regression analysis. The dataset included various attributes, such as nationality, job title, years of experience, and number of surgeries, as well as multiple ratings from different stakeholders, such as patients, nurses, and supervisors. The results showed that the set of attributes was divided into three groups: the original feature set, the 3-star

feature set, and the best Lasso features [6]. The current study focuses on analyzing the effect of feature selection on clustering accuracy. Several methods for feature selection are compared to determine the most appropriate methods for grouping physicians according to different performance criteria. Regression methods were applied to these attributes in Ghazzawi et al.'s study to identify the most influential attributes, which this study will use in clustering to test the accuracy of the resulting classifications. This research aims to improve administrative decision-making within healthcare organizations by providing more accurate physician ratings. By analyzing this data, a deeper understanding of the differences between physicians and the factors influencing their performance can be achieved, helping to improve decision-making, evaluation strategies, and professional development in healthcare organizations. This study may also contribute to improving predictive models used to evaluate physicians, enhancing the ability to allocate resources more efficiently, guiding training programs, and designing physician evaluation policies based on accurate and reliable data.

### A. Significance of the Study

This study is of great importance in the context of improving physician performance evaluation in healthcare institutions using the clustering method. With the rapid development of technology and big data, it has become necessary to apply advanced data analysis methods such as clustering to better understand the patterns and factors influencing physician performance. This study contributes to:

*1) Improving assessment accuracy:* By analyzing diverse data and using the clustering method, the most influential attributes in physician performance evaluation are identified, enhancing the accuracy of evaluations and helping improve decision-making.

*2) Supporting advanced data analytics in healthcare:* The study promotes the use of big data-based data analytics methods, such as clustering, to improve evidence-based healthcare decisions.

*3) Discovering hidden patterns*: The study helps uncover unseen patterns that may contribute to improving the effectiveness of predictive models, contributing to improving the quality of healthcare.

*4) Achieving strategic improvements:* The study provides strategic insights for improving training programs, allocating resources, and developing effective policies for evaluating physicians based on the most influential attributes.

### B. Objectives

*1) Identifying the most important attributes for physician performance evaluation:* The study aims to identify the key attributes that should be emphasized when applying clustering to improve performance evaluation.

*2) Comparing the impact of clustering on the accuracy of predictive models:* The study aims to compare the impact of clustering on improving the accuracy of predictive models for evaluating physician performance and provide recommendations for its use.

*3) Analyzing the relationship between various traits and physician performance:* The study aims to analyze the relationship between traits extracted from the data (such as years of experience, job title, number of operations) and physician performance in various assessments.

*4) Achieving strategic improvements in healthcare institutions:* The study aims to provide strategic insights for improving resource allocation, training programs, and policy development that impact physician performance evaluation based on clustering results.

*5) Uncovering patterns and factors influencing performance evaluation:* The study aims to uncover hidden patterns that may contribute to improved decision-making related to physician performance in healthcare.

### C. Research Problem

The study's problem is to identify the most appropriate attributes to focus on when evaluating physician performance using the clustering method. There is an urgent need to understand the relationship between various attributes (such as nationality, job title, years of experience, number of operations, and patient evaluation) and physician performance. Furthermore, the study raises questions about the extent to which the clustering method can improve the accuracy of predictive models and discover effective patterns that contribute to making accurate data-driven healthcare decisions. In this context, a set of questions guides this study:

- What are the most important attributes in evaluating physician performance when applying the clustering method?

This question aims to identify the attributes that primarily contribute to evaluating physician performance after analyzing different datasets. This contributes to improving evaluation accuracy and ensuring that the models used reflect the most influential attributes.

- What are the differences between different datasets (original attributes, 3-star attributes, and the Lasso model) in terms of their impact on physician performance evaluation?

This question aims to compare the impact of the original attributes, the attributes extracted through 3-star regression, and the Lasso predictive model on performance evaluation, and to determine which dataset provides more accurate and reliable results.

- Can using the clustering method reveal new patterns in physician performance evaluations that were not apparent using traditional methods?

This question focuses on exploring the ability of the clustering method to discover new patterns in data that may contribute to improving decisions related to physician performance evaluation, which may not be apparent using traditional methods.

- How can clustering results be used to improve physician training programs and resource allocation within hospitals?

This question aims to examine how clustering results can be applied to improve training programs and resource allocation within hospitals, leading to improved physician performance and the delivery of high-quality healthcare.

- What is the relationship between the attributes extracted from the datasets and physician performance in various assessments (such as the evaluations of patients, nurses, and supervisors)?

This question helps examine the relationship between attributes such as years of experience, number of operations, and physician performance as evaluated by different stakeholders, such as patients, nurses, and supervisors.

Through these questions, the study aims to provide a comprehensive vision on how to improve physician performance assessment using the clustering approach, which enhances the ability to make accurate and reliable decisions based on pivotal data, thus improving overall performance in the health system.

### D. Research Contributions

*1) Comparison of different datasets:* This study contributes by providing a detailed comparison between three datasets collected from a hospital in Egypt, including the original attributes, attributes extracted using 3-star regression, and the Lasso model. This helps identify the most effective attributes for evaluating physician performance.

*2) Expanding understanding of clustering in healthcare:* The study provides scientific insights by applying clustering to physician performance evaluation, demonstrating how this approach can improve results by identifying the most influential patterns and attributes.

*3) Analyzing the relationship between different attributes and performance:* By examining the relationship between attributes such as nationality, job title, years of experience, and other attributes, and the varied performance of physicians in different evaluations, this study contributes to providing new insights to support decision-making in healthcare institutions.

*4) Enhancing predictive capability in healthcare models:* By using advanced methods such as clustering, the study contributes to improving predictive models that can support strategic decisions for physicians and hospital management.

### E. Paper Layout

The paper's reminder is organized as follows: in Section II, a Related works is presented; in Section III, the Methodology that includes Datasets Used, Methodology for Determining the Optimal Number of Clusters, Finding the Optimal Number of Clusters, Analysis of clustering results and appropriate decisions, in Section IV, The research work is concluded by expressing direction, in Section V, Study Limitations, in Section VI, Future work, which will open new avenues of exploration and discovery, for upcoming research work.

## II. Literature Review

Many previous studies have focused on evaluating the professional performance of physicians using various data analysis techniques, with an emphasis on selecting the most influential attributes in the evaluation process.

Campbell et al, aimed to evaluate the performance of physicians in the United Kingdom through a cross-sectional survey involving patients and colleagues, and the data were analyzed using principal component analysis and regression. The results confirmed that communication skills, clinical competence, and professionalism, along with age, gender, and specialty, play a fundamental role in assessing medical performance [7]. Mirfat et al. confirmed that individual, psychological, and organizational factors play a crucial role in understanding physician performance. Psychological factors were found to have the strongest direct influence, while organizational factors showed a positive but statistically insignificant effect [8]. On the other hand, Cassel et al. demonstrated that intrinsic motivation, such as achievement and patient appreciation, along with extrinsic incentives such as financial rewards and recognition, significantly influence physician motivation levels [9]. In another study, Cola et al. demonstrated that the success of physician-scientists depends on a range of factors, including role balance, autonomy, organizational support, teamwork, mentorship, and the ability to build relationships. These multidimensional factors are essential for understanding and improving physician performance in academic medical settings [10]. Jin et al. also noted that factors influencing healthcare worker performance, such as burnout and anxiety, were analyzed before and after the COVID-19 pandemic, providing deeper insights into improving physician performance [11]. In addition, William et al. identified 22 key variables that influence medical lecturers' performance, most notably leadership, commitment, and credit scores, reflecting the complexity of the interrelationships that govern the performance evaluation process [12]. Overeem et al, used multi-source feedback (MSF) tools to evaluate physicians based on patient ratings, colleague assessments, and the physicians' self-evaluations. The results showed significant differences between the physicians' self-evaluations and the ratings provided by others, indicating the importance of using multi-source data to analyze performance [13]. Bindels et al, a professional performance evaluation system for physicians was implemented in a Dutch medical center through peer conversations based on the principles of appreciative inquiry and continuous feedback. The study emphasized the importance of continuous professional development and periodic feedback in improving physicians' performance [14]. Study by Ho and Baker: The General Medical Council (GMC) has developed a framework for good medical practice, which includes assessing physicians' performance every five years by measuring knowledge, communication skills, decision-making, and patient-centered medical practice [15]. Dias et al, a systematic review of 69 studies addressing the use of machine learning in evaluating physician competence was conducted, analyzing the impact of various features on professional performance using decision trees, support vector machines, and random forests. The study found that the specialties of surgery and radiology were the most affected by these technologies and emphasized that feature selection significantly impacts the accuracy of the models [16]. As Ghazzawi et al. focused on analyzing data from an Egyptian hospital using regression techniques to examine the attributes that most influence physician performance. The datasets

included attributes related to physicians, such as age, nationality, job title, years of experience, number of publications, and surgeries, as well as various ratings from patients, nurses, and human resources. The first dataset consists of the original dataset, which contains a wide range of attributes potentially relevant to performance evaluation. The second dataset represents a selection of attributes extracted using regression and receiving a 3-star rating. The third dataset includes the most effective attributes in predictive models, such as the Lasso model. The study focuses on this comparison between the different datasets, aiming to highlight the attributes that most significantly influence the clustering results and physician performance evaluation. The results demonstrate that regression analysis can be an effective tool for healthcare administrators to help reduce medical error rates, providing a framework for data-driven decision-making. Table I summarises the results of all the regression models in the Ghazzawi et al. study, which we will rely on in our current study [6].

TABLE I. IMPORTANCE OF FEATURES IN PREDICTING THE THREE MODELS, ADAPTED FROM STUDY [6]

| Attribute/Model | Lasso Regression | Ridge Regression | Linear Regression |
|---|---|---|---|
| Nationality | (+) *** | (+) *** | (+) * |
| Position title | (-) *** | (-) *** | (-) ** |
| Years of Experience | (+) ** | (+) ** | |
| Number of Publications | (+) * | (+) * | |
| Number of operations | (-) * | (-) * | (-) *** |
| Age Groups | | (-) *** | |
| Gender | | (-) * | |
| Department | | (+) *** | |
| Patient Assessment | | (+) * | |
| Nurses' Assessment | | (-) * | |
| HR Assessment | | (-) *** | |
| Supervisor Assessment | | (-) * | |
| Number of complaints | | (-) * | |

Ghazzawi et al.'s study contributed to the extraction of features, as shown in Table I. All features in the models used, with 3 stars representing the most important, were evaluated with the Lasso model receiving the highest rating. Although previous studies have addressed many factors influencing physician performance, aspects still have not been thoroughly studied, such as the impact of feature selection on classification accuracy using clustering methods. This study seeks to bridge this gap by analyzing different methods to identify the most influential features. This can then cluster and make appropriate decisions for each group, contributing to improved recruitment, professional development, and administrative decision-making within healthcare organizations

### A. Research Gap

*1)* Despite previous efforts to evaluate physician performance using traditional methods such as multi-source (MSF) assessments and questionnaires, there are clear research gaps that warrant further exploration. This study seeks to address these gaps, most notably.

*2)* The Lack of Use of Artificial Intelligence and Machine Learning Techniques in Physician Evaluation.

*3)* Most previous studies focus on traditional assessments such as patient surveys or peer reviews, without incorporating advanced techniques such as clustering to uncover hidden patterns and objectively analyze physician performance.

*4)* Lack of In-Depth Analysis of the Impact of Feature Selection on Clustering Accuracy.

*5)* Although some studies have used data analysis techniques, there is a dearth of research comparing different feature selection methods such as LASSO, regression, and dimensional analysis, and their impact on physician classification accuracy.

*6)* Limited Research on the Application of Clustering in the Healthcare Sector.

*7)* K-Means and other clustering methods have been applied in many fields, but their use in classifying physicians based on professional performance remains limited, leaving a gap in understanding how to improve evaluation quality using these techniques. Failure to Consider External Factors Influencing Ratings.

*8)* Some studies indicate that ratings based on patient and peer feedback may be influenced by socioeconomic factors rather than actual physician performance, calling for the development of more accurate models to mitigate bias.

*9)* Lack of Empirical Validation of the Impact of Ratings on Improving Healthcare Quality.

*10)*Most research is limited to data analysis without examining the actual impact of using the resulting ratings to improve management decisions and develop physician training programs.

### B. Study's Contribution to Bridging the Gap

*1)* Applying the K-Means algorithm to classify physicians based on objective performance criteria.

*2)* Comparing different feature selection methods to determine the most accurate physician classification.

*3)* Studying the impact of various factors on the accuracy of assessments to provide a fairer and more objective model.

*4)* Providing recommendations for the practical application of clustering results to improve healthcare quality and administrative decision-making within medical institutions.

## III. METHODOLOGY

In this study, the K-means algorithm will be applied using Python tools to cluster physician performance evaluation data, relying on three different datasets derived from the regression results in the study [6]. The study aims to analyze the effect of feature selection on the accuracy and effectiveness of the clustering process. The data was extracted from a hospital in Egypt and processed to remove outliers to ensure data quality.

### A. Datasets Used

The study will rely on three sets of features: original features, 3-star-rated features, and Lasso-based features. Each set is detailed below:

*1) Group 1:* Original Attributes: This set contains all the original attributes collected without any dimensionality reduction. The attributes include Age, nationality, job title, years of experience, number of publications, operations, department, patient evaluation, nurse evaluation, human resources evaluation, supervisor evaluation, and complaints.

*2) Group 2:* Selected 3-Star Attributes: This group is based on attributes rated three-star according to their importance in the previous study analysis [6], shown in Table I. They include nationality, job title, number of operations, age groups, department, and HR assessment.

*3) Group 3:* Attributes Selected Using the Lasso Model: Lasso regression analysis was applied to identify the most influential attributes in the model, resulting in the selection of a smaller set of attributes: Nationality, Job Title, Years of Experience, Number of Publications, and Number of Operations.

### B. Methodology for Determining the Optimal Number of Clusters (k)

*1) Elbow method:* This method will be used to analyze the variance within clusters and identify the inflection point that represents the balance between the number of clusters and internal consistency.

*2) Silhouette index:* This method will be used to assess the quality of clustering based on how distinct the clusters are from each other.

### C. Finding the Optimal Number of Clusters

This study will apply unsupervised learning using the k-means algorithm to identify core clusters that may reveal common patterns in professional profiles, practice patterns, or outcomes. The features were divided into three groups, including all original features, 3-star features, and the best Lasso features, as shown in Figures [1], [2] and [3]. This division can provide valuable insights for improving resource allocation and designing effective training programs. Importantly, this approach has the potential to significantly improve the quality of healthcare, positively impacting patient outcomes. To achieve this, a systematic approach based on data-driven clustering techniques was adopted, as described in the following sections.

*a) Using all original features (Optimal k=3):* Fig. 1 presents the number of clusters (k=3). There is a clear distribution of the three clusters. This indicates that all original features carry strong information, allowing for the formation of three distinct clusters. This reflects a strong ability to differentiate between data, achieving high clustering accuracy. The original features are best suited when you have a diverse dataset and need good partitioning between clusters.

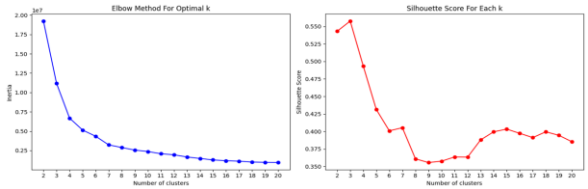


Fig. 1. Elbow Method and Silhouette Scores on original features for finding optimal k.

*b) Using 3-star features (Optimal k=2):* Fig. 2 shows the number of clusters (k=2). There is a less diverse distribution of clusters compared to all original features. The optimal number of clusters is only 2, indicating that the "3-star" features may lack some detail that helps differentiate between data classes. This simplification may be useful in some cases if the goal is to reduce complexity, but at the expense of some accuracy. These features may be useful if you want to simplify data or if you have a complex problem that requires less complex clustering.

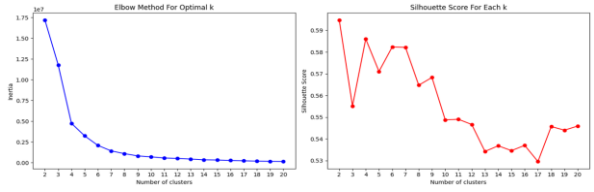


Fig. 2. Elbow Method and Silhouette Scores on 3-star features for finding optimal k.

*c) Using Lasso's best features (Optimal k=3):* Fig. 3 provides the number of clusters (k=3). Like the original features (k=3). The features selected by Lasso appear to select only the most important factors affecting clustering, allowing you to maintain high accuracy while reducing the number of features. It can be argued that Lasso reorders the features in a way that preserves essential details without adding additional complexity.

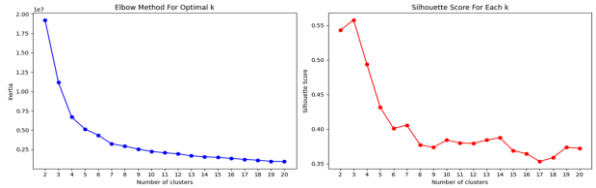


Fig. 3. Elbow Method and Silhouette Scores on Lasso's best features for finding optimal k.

The results show that both the original features and the best features selected by the Lasso model performed best at the optimal number of clusters, indicating their ability to provide accurate data segmentation. The original features provided the best cluster separation, reflecting high clustering accuracy. In contrast, the Lasso features offered an effective balance between reducing complexity and maintaining accuracy, achieving results close to those achieved using all the original features, but with fewer features.

The "three-star" features were simplified and resulted in a smaller number of clusters, which may be useful in some cases where data complexity reduction is required. However, this simplification may result in the loss of important details that may be necessary to understand subtle patterns in the data.

### D. Results

The K-Means algorithm was applied to three different datasets, each with a distinct set of features. The optimal number of clusters was determined using both the Elbow method and the Silhouette index to evaluate the effectiveness of each feature set in the clustering process.

Group 1: Original Features

The results, as shown in Fig. 1, indicate that the optimal number of clusters was k=3. The Silhouette Index also recorded its highest value at this number, indicating that the original features were able to differentiate physicians into three distinct groups.

Group 2: Selected Features (Three Stars)

The results, as shown in Fig. 2 for this group, showed that k=2 was the optimal number of clusters, achieving acceptable performance. However, the Silhouette index was lower than the first group. This indicates that this group tends to oversimplify the data, which may lead to the loss of some fine detail.

Group 3: Lasso Features

The results point as Fig. 3 to k=3 as the optimal number of clusters, with a Silhouette index close to the original grouping. This indicates that the selection of these features reduced the number of variables while maintaining classification quality and accuracy.

Overall, the results indicate that feature selection has a direct impact on the number of resulting clusters and the accuracy of the clustering. Both the original and Lasso features provided accurate and meaningful clustering, while the "three-star" grouping produced a simpler model. These results demonstrate the potential for leveraging feature selection techniques to customize assessment methods more accurately and effectively in healthcare contexts. Based on these results, the study recommends using the original features due to their ability to achieve the highest clustering accuracy and distinguish clusters more clearly, making them the ideal choice when more detailed data analysis is required.

*E. Analysis of Clustering Results and Appropriate Decisions*

Based on The original features were adopted due to their demonstrated remarkable effectiveness in enhancing the accuracy of the clustering process and their ability to more clearly demonstrate the variation between groups, making them the ideal choice for analyzing accurate data and making personalized decisions at the level of each physician. Based on statistical analysis, it was possible to identify distinctive characteristics for each group of physicians, enabling the formulation of administrative and development decisions tailored to the nature of each group's performance.

*1)* Cluster 1 – Young and Mid-Earned Physicians.

Distinctive Characteristics:

Average age: 49.7 years (youngest group).

Average years of experience: 24.7 years.

Average ratings from patients, nurses, and management: High (between 4.44 and 4.84).

Average number of publications: 78.5 papers.

Medicinal error rate: 0.041 (relatively low).

Average number of operations: 800 operations.

Appropriate Decisions:

- Invest in their professional development by providing advanced training courses and mentoring programs from more experienced physicians.
- Encourage scientific research by providing grants and support for the publication of their research, as they have a good publication rate, but lower than the second group.
- Increase their administrative responsibilities, as they have good patient and nurse reviews, potentially qualifying them for future leadership roles.
- Motivate them financially and administratively by offering incentives for excellent performance, as they could be the future of the medical institution.

*2)* Cluster 2 – The most experienced and most surgically active physicians.

Distinctive characteristics:

Average age: 62.1 years.

Average years of experience: 37.1 years (the most experienced group).

Average ratings are very high (between 4.44 and 4.85).

Average number of publications: 136.7 papers (the highest among the three groups).

Medicinal error rate: 0.040 (the lowest among the groups).

Average number of operations: 889 operations (the highest among the groups).

Appropriate decisions:

- Keep them in leadership and supervisory roles given their extensive experience and high ratings.
- Gradually reduce the workload on them and invest their expertise in training younger physicians.
- Encourage them to focus on scientific research and participate in medical conferences to enhance the hospital's standing.
- Developing their incentive programs, such as granting job benefits to highly experienced physicians to increase their loyalty to the organization.

*3)* Cluster 3 – Physicians with the Least Research Involvement.

Distinctive Characteristics:

Average Age: 60.7 years.

Average Years of Experience: 35.7 years.

Average Ratings High (between 4.51 and 4.86).

Average Number of Publications: 39.6 (lowest among the three groups).

Mean Medical Error Rate: 0.047 (higher than the other two groups).

Average Number of Operations: 807.

Appropriate Decisions:

- Increase their participation in scientific research, as their publication rate is lower than that of Cluster 2. This can be achieved by providing research support or imposing research requirements for senior positions.
- Improve their medical skills and reduce errors through specialized training programs.
- Increase their involvement in academic and professional activities such as workshops and medical conferences to enhance their research experience.
- Directing them to supervise new physicians instead of focusing only on surgical procedures, to benefit from their extensive experience in training and guidance.

Finally, this analysis helps guide recruitment, training, and professional development strategies for each group of physicians more accurately. Table II provides a summary of the proposed decisions and appropriate actions for each group of physicians.

TABLE II. A SUMMARY OF THE RECOMMENDATIONS FOR EACH CLUSTER

| Cluster | Main Characteristics | Proposed Decisions |
|---|---|---|
| Cluster 1 (young, intermediate-level physicians) | Younger age, good ratings, moderate number of research assignments, good number of operations | Professional training and development, encouragement of scientific research, management roles |
| Cluster 2 (more experienced and most surgically active physicians) | Highest experience, highest number of operations, highest number of research, fewest errors | Supervisory roles, gradual reduction of operations, promoting scientific research, financial incentives |
| Cluster 3 (physicians least involved in scientific research) | Good experience, lowest amount of research, relatively high number of errors | Professional research encouragement, training to reduce errors, integration into supervision and teaching |

*4) Comparison of clustering performance and results:* Comparing the results, the second cluster (Cluster 2) is the most experienced and most engaged in scientific research, making it ideal for leadership and mentoring roles. The first cluster (Cluster 1) is characterized by physicians in early or mid-career, making it ideal for investing in training and professional development. The third cluster (Cluster 3) includes physicians with extensive experience but less research activity, indicating a need to enhance their involvement in academic research and improve their skills.

## IV. CONCLUSION

This study indicated that selecting appropriate features directly affects the number of clusters resulting from clustering. The results showed that all original features and the best Lasso features resulted in an optimal number of clusters with a value of k=3, indicating that these features retained the essential information needed to distinguish between different physician classes. On the other hand, using simplified features reduced the number of clusters to k=2, which may be useful in some cases, but may result in the loss of some important details. In summary, this study highlights the importance of choosing appropriate features when applying clustering techniques and provides a framework that can be used in future research to analyze staff performance in medical and other fields. Furthermore, the results showed that the original features provide a clear distribution of physicians based on experience, age, and number of operations, facilitating personalized recommendations for each group. The results of this analysis can be used to support hospital decision-making in terms of developing training programs, assigning tasks, and identifying research opportunities for physicians based on their current performance.

Based on these results, the hospital recommends using cluster analysis to improve physician management and develop motivation and training programs tailored to each group, ensuring maximum utilization of available human resources.

## V. STUDY LIMITATIONS

This study focuses on analyzing the impact of feature selection on the accuracy of physician clustering according to different performance criteria, using the K-Means clustering algorithm. However, some limitations should be taken into account:

*1) Data limitations:* The study relies on data from multiple sources, including patient reviews, peer evaluations, and administrative evaluations. This data may not be comprehensive of all aspects of physicians' professional performance, and its accuracy depends on the objectivity of the evaluators.

*2) Sample scope:* The data were collected from a single hospital in Egypt, which may affect the generalizability of the results to other medical institutions with different evaluation systems or work environments.

*3) Influence of external factors:* External factors, such as the socioeconomic environment or the nature of the health system, may affect the clustering results. These factors were not directly considered in this study.

*4) Methodology used:* The study relies on the K-Means clustering algorithm, which requires pre-determining the number of clusters. This may affect the accuracy of the results if the optimal number of clusters is not carefully selected.

*5) Lack of validation of practical impact:* The study is limited to analyzing data and testing the accuracy of the resulting classifications, without empirically validating the impact of these classifications on improving healthcare quality or actual physician performance.

## VI. FUTURE WORK

Further Analysis of Selected Features: Additional studies could be conducted to analyze how the selection of different features affects clustering performance, especially in fields other than the healthcare sector.

Testing advanced clustering techniques: The use of other methods, such as hierarchical clustering or deep learning algorithms, could be studied to improve clustering results.

Scaling up the study: The study could be expanded to include other hospitals and different medical communities to compare the results and determine their generalizability.

Analyzing the impact of behavioral factors: Additional data, such as physician satisfaction and burnout levels, could be incorporated, along with their impact on the performance of different groups.

Combining cluster analysis with classification techniques: A model combining clustering and predictive classification could be developed to improve the accuracy of physician management recommendations.

This study represents a first step toward improving human resource management in hospitals using modern data analysis techniques. Further research is recommended to improve these models and enhance the accuracy of management recommendations in the future.

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# Exploring Digital Insurance Solutions: A Systematic Literature Review and Future Research Agenda

Anni Wei, Yurita Yakimin Abdul Talib*, Zakiyah Sharif
Tunku Puteri Intan Safinaz School of Accountancy College of Business, Universiti Utara Malaysia, Sintok, Malaysia

***Abstract*—The purpose of this study is to explore the antecedents for the adoption of digital insurance solutions and to present current research trends and future research agendas based on a systematic literature review. The findings revealed key motivators for the adoption of digital insurance solutions, such as trust, perceived usefulness, ease of use, performance and effort expectancy, social influence, subjective norms, self-efficacy, system quality, and attitudes. Meanwhile, the key inhibitors include perceived risk, privacy concerns, complexity, and technology anxiety. The study shows that current research themes primarily focus on the online insurance sector, while lack of attention to emerging technologies. Although the Technology Acceptance Model (TAM) being the most widely applied theory in digital insurance adoption studies, its explanatory power needs to be enhanced by introducing new theories. Moreover, most research samples consist of insurance consumers, with less attention paid to user groups excluded from financial services. Questionnaires and Structural Equation Modeling (SEM) are commonly used methods, but still have limitations when dealing with large samples and complex behavioral changes. This study provides guidance for governments in promoting the implementation of digital insurance solutions, alongside strategic support for insurers to optimise user experience and enhance industry competitiveness.**

***Keywords*—Digital insurance; Technology Acceptance Model; antecedents of adoption; systematic literature review; future research agenda**

## I. Introduction

As an important pillar of socio-economic and personal well-being, the insurance industry has been at the forefront of technological innovation and digital transformation. With the rapid development of information and communication technology (ICT), insurance companies are actively utilising various digital tools to enhance service quality and market competitiveness [1]. Digital insurance has excelled in areas such as risk assessment, claims processing, and customer interaction. Digital insurance, which refers to the development, delivery, and management of insurance products and services based on digital technology [2], encompasses a variety of digital solutions such as online policy administration, mobile insurance platforms, blockchain-based insurance contracts, and risk assessment powered by artificial intelligence. Nowadays, technology-enabled insurance is an emerging force that drives industry transformation and enhances insurers competitiveness.

At present, the promotion and application of digital insurance still encounter many challenges. Although digital technology has injected innovation into the insurance industry, its development is susceptible to the rapid iteration of new technologies and environmental changes. On the one hand, for the existing user base, consumers experienced difficulties in comparing products or services in previous insurance transactions. The situation has changed with the rapid development of technology. Nowadays, consumers can use digital platforms to compare prices and information anytime and anywhere to make smarter and better choices. Consumers' demand for convenience and real-time interaction is also on the rise, thus increasing the pressure on insurers [3]. Failure to deliver a superior digital customer experience may cause customers to turn to competitors who can better meet their needs. Therefore, for insurers that are seeking rapid growth, deep insights into consumer behavior and preferences as they respond to technological change and evolving needs are key to competitively winning the market. On the other hand, many potential user groups are less receptive to digital insurance solutions, still preferring traditional offline services or transactions through insurance agents [4]. Especially in less-developed regions, the lack of financial inclusion makes it difficult for some groups to access the insurance market. In some emerging markets or remote areas, while digital insurance solutions can overcome geographical constraints, the lack of digital infrastructure is a critical barrier to their further penetration [5]. Thus, the resistance and potential opportunities for digital insurance adoption should be explored in depth.

A systematic literature review (SLR) is necessary in order to address the challenges encountered in the diffusion and adoption of digital insurance solutions. The SLR approach not only provides a comprehensive overview of research trends in the insurance field but also offers strategic reference for the practice of the field. In contrast, singular studies are usually incapable of covering the multidimensional aspects of the field comprehensively. Digital insurance-related research has been ongoing for over a decade. However, there are limited SLRs on the adoption of digital insurance solutions. In addition, emerging technologies such as blockchain, artificial intelligence, and Internet of Things (IoT) are changing the research priorities and directions in the insurance industry [6]. Hence, improving users' acceptance and user experience towards digital insurance solutions remains a priority that needs to be addressed. The authors sorted out and analysed the antecedents of digital insurance solutions adoption through a SLR, aiming to determine the factors influencing consumer acceptance. This study performing topic searches and article screening in mainstream academic databases (i.e., Web of Science and Scopus). A systematic review of relevant literature was conducted to answer the following research questions (RQs):

*Corresponding Author

RQ1: What is the extent of research done to date pertaining to the adoption of digital insurance solutions?

RQ2: What are the key antecedents of the adoption of digital insurance solutions?

RQ3: What is the current research landscape related to the adoption of digital insurance solutions?

RQ4: What are the future research directions in areas related to the adoption of digital insurance solutions?

This study helps to provide a concrete theoretical basis and strategic decision for academics, policymakers, and insurers for deepening their understanding of digital insurance adoption behaviors. The authors believe that this study could inspire more researchers to focus on and explore the different preferences and choices consumers have in relation to digital insurance solutions.

This study is organised into five parts. Section II introduces the literature review methodology; Section III summarises the key results of the literature review; Section IV discusses the findings and proposes a future research agenda; and finally, Section V concludes this study.

## II. Methodology

### A. Review Method

The SLR is a rigorous research methodology that enables a comprehensive analysis and summary of existing research in a structured and transparent manner [7]. It is regarded as one of the most informative and scientifically sound types of literature review methods. Therefore, this study adopted the SLR approach to review the literature in the field of digital insurance adoption.

### B. Review Process and Database Search

The authors searched the articles published from 2000 to 2024, a critical period during which the insurance sector was impacted by technological innovation and digital development. To ensure the quality and representativeness of the articles, the authors focused the searches on Web of Science and Scopus databases. These two databases cover many subject areas and are famous for their high-quality peer-reviewed research articles [8]. The database search for this study was conducted in December 2024.

The literature screening process strictly followed the guidelines of the PRISMA model. This model is widely used in SLR studies due to its advantages in terms of transparency, reproducibility, and methodological consistency [9]. The authors constructed keyword strings based on expert opinions in related fields. Subsequently, articles related to digital insurance adoption were screened by combining synonyms and related terms using Boolean logic operators. Fig. 1 presents the screening process used according to the PRISMA model, alongside the explicit inclusion and exclusion criteria set during the search process. Eventually, the authors obtained 28 articles that fit the study topic.

## III. Results

### A. Most Cited Studies

The citation rate is a key indicator of a study's impact, and a higher number of citations usually indicates that the study has greater influence and visibility in the academic community [10]. To assess the core literature on digital insurance adoption, this study identified the five most highly cited studies by analysing the number of citations. To further quantify the academic impact of the literature, the authors calculated the average number of citations by dividing the total number of citations of a study by the number of years it has been published as a measure of the frequency of citations per year. The review process shows that Heinze et al. [11], is the most cited study in terms of the number and frequency of citations. Table I lists the top five studies with the highest number of citations. The authors believe these studies can serve as a basis for future research in digital insurance.

TABLE I. Five Most Cited Studies in the Field of Adoption of Digital Insurance Solutions from 2000 to 2024

| Authors | Total citations | Citation per year |
|---|---|---|
| Heinze et al. [11] | 96 | 13.71 |
| Gebert-Persson et al. [12] | 50 | 10 |
| Khare et al. [13] | 38 | 3.17 |
| Gowanit et al. [14] | 37 | 4.63 |
| Wang and Lu [15] | 34 | 3.4 |

Source: Based on Google Scholar as of December 2024.

### B. Geographical Location of Previous Studies

Significant geographical differences exist in global research on the adoption of digital insurance solutions, as shown in Fig. 2. Asia, encompassing ten countries or regions such as India, China, and Taiwan, has the leading research concentration. Europe, covering six countries including Spain, Finland, and Germany, has the next highest number of studies. Fewer studies were conducted in Africa and North America. Among the countries or regions, India and Spain have the highest number of studies (n=4). These studies demonstrate the exploration of the insurance industry's digitisation in different regions of the world.

### C. Antecedents of Digital Insurance Solutions Adoption

This study systematically sorted out the antecedents of user acceptance of digital insurance solutions and categorised them into two categories: motivators and inhibitors. While motivators are positive forces that drive users to accept or use digital solutions, inhibitors are negative factors that prevent users from adopting such technology.

*1) Motivators*: Table II presents the top 10 positive factors influencing the acceptance of digital insurance solutions based on the frequency of occurrence. The factors are trust, perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, social influence, subjective norms, self-efficacy, system quality, and attitude.

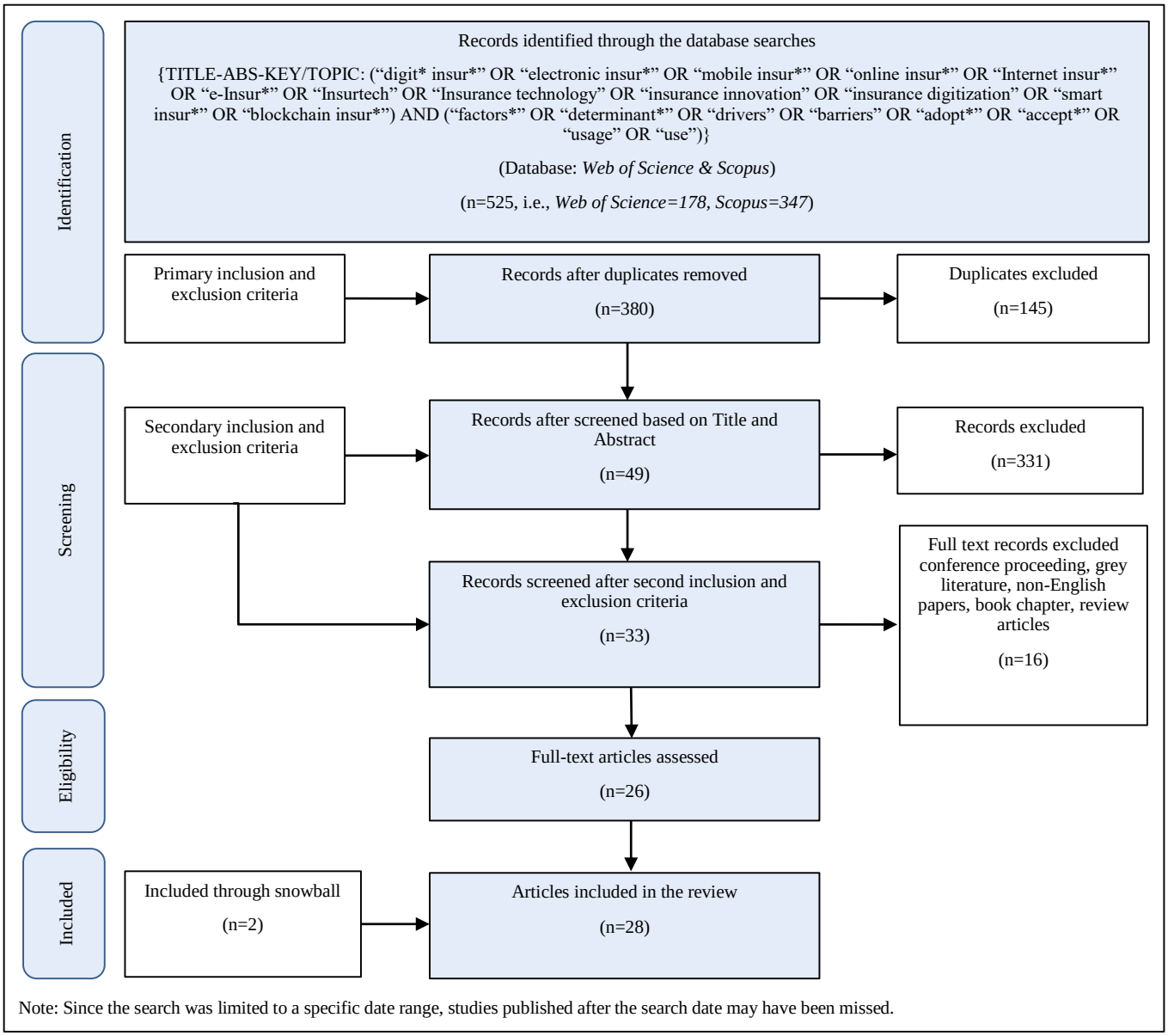


Fig. 1. PRISMA flowchart.


Fig. 2. Geographical locations of the reviewed studies.

*2) Inhibitors*: The factors that negatively affect the acceptance of digital insurance solutions are shown in Table III. Compared to motivators, inhibitors have been less researched and only mentioned in some studies. Therefore, this study lists the top four factors that occur with the highest frequencies, namely, perceived risk, privacy concerns, perceived complexity, and technology anxiety.

### D. Profiles of Studies

*1) Themes of reviewed studies*: Based on the literature review, the authors identified the main trend of research themes in the field of digital insurance adoption, as shown in Fig. 3. Existing research focuses on areas such as online insurance, Chatbot-based insurance, e-insurance, and mobile insurance. However, the research on technologies such as telematics and wearable devices in digital insurance are still relatively less explored.

TABLE II. MOTIVATORS OF DIGITAL INSURANCE ADOPTION

| Factors | Definition | Citation |
|---|---|---|
| Trust | The degree to which an individual perceives and believes in the reliability, integrity and trustworthiness of another person, organization, or system. | [12], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23] |
| Perceived usefulness | An individual's subjective evaluation of whether the use of a particular object, service or technology is perceived as having real value and benefit. | [12], [14], [18], [19], [22], [24], [25], [26] |
| Perceived ease of use | An individual's subjective assessment of how easy or effortless it is to use a particular technology, product, or system. | [12], [14], [18], [19], [22], [25], [26], [27] |
| Performance expectancy | The benefits or performance that an individual expects from the use of a technology or service. | [17], [20], [23], [28], [29], [30] |
| Effort expectancy | The degree to which an individual expects effort to be required to complete a task when using a particular technology, system or service. | [17], [20], [23], [28], [29], [30] |
| Social influence | The impact that the words, attitudes, and behavior of others have on an individual's perceptions, decisions, and behavior. | [17], [20], [23], [28], [29], [30] |
| Attitude | An Individual's positive or negative evaluations of the use of a technology or service. | [12], [16], [19], [22], [26], [31] |
| Subjective norm | An individual's perceived social pressure, i.e. the extent to which others expect them to engage or not engage in a behavior. | [14], [18], [22], [26], [27] |
| Self-efficacy | An individual's understanding and beliefs in his or her skills and capability to perform a task given. | [14], [18], [29], [32] |
| System quality | The overall technical level and performance of an information system in terms of functionality, reliability, usability, and responsiveness. | [15], [28], [29], [33] |

TABLE III. INHIBITORS OF DIGITAL INSURANCE ADOPTION

| Factors | Definition | Citation |
|---|---|---|
| Perceived risk | An individual's subjective perception or awareness of the potential risks associated with a behavior, decision, or product. | [22], [23], [24], [28], [29], [32] |
| Privacy concern | The potential threats and harm that an individual or organization may face when processing, collecting, storing, and sharing personal information. | [14], [21], [30], [33] |
| Perceived complexity | An individual's perceived level of complexity in relation to a thing, concept, or task. | [15], [27] |
| Technology anxiety | The nervousness, anxiety or worry that individuals feel when faced with new technologies. | [21], [27] |

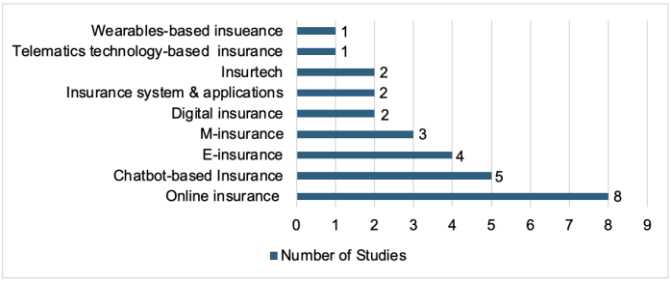


Fig. 3. Themes of previous studies

Source: Compiled by authors

*2) Theories and models*: Based on the literature review, the authors found that 18 of the 28 studies used a theoretical framework or model, as shown in Fig. 4. One of the most used is Technology Acceptance Model (TAM). TAM, a model proposed by Davis et al. is used to explain user acceptance behavior towards new technologies through two core variables: perceived usefulness and perceived ease of use [34]. In addition, the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. is the second most used theory or model. The UTAUT model integrates multiple technology acceptance theories and emphasises the joint impact of performance expectancy, effort expectancy, social influences, and facilitating conditions on user behavior [35]. DeLone and McLean's Information Systems Success Model (D&M Model) is this field's third most-used theoretical model. The D&M Model, which includes system quality, information quality, and service quality, provides a tool for measuring users' usage of the system and user satisfaction [36]. However, not all studies used existing theoretical frameworks. Some studies did not

cite traditional models, and other studies developed new models based on research needs.

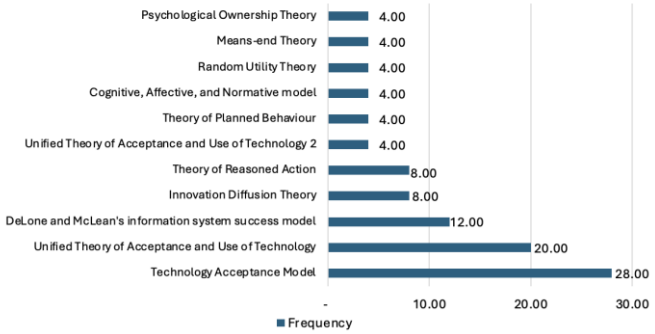


Fig. 4. Theories and models used in past studies.

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*3)* Methodology Overview

*a) Statistical data analysis tools and techniques*: This study also reviewed the tools and techniques used for statistical analysis in the literature, as shown in Table IV. Structural Equation Modeling (SEM), Partial Least Squares Structural Equation Modeling (PLS-SEM), and Multinomial Logistic Regression are the main data analysis techniques used in the field of digital insurance.

TABLE IV. DATA ANALYSIS TOOLS AND TECHNIQUES USED

| Methods | Citations |
|---|---|
| Structural Equation Modeling (SEM) | [12], [15], [16], [19], [22], [24], [26], [29], [33] |
| Partial Least Squares Structural Equation Modeling (PLS-SEM) | [17], [18], [20], [23], [28], [31] |
| Structural Equation Modeling-Artificial Neural Network (SEN-ANN) | [27] |
| Structural Equation Modeling (SEM) | [37] |
| Partial Least Squares Structural Equation Modeling (PLS-SEM) | [25], [32], [38] |
| Logistic Regression | [13], [30] |
| Multinomial Logistic Regression | [38] |
| Multiple Regression | [32] |
| Bivariate Probit regression | [32] |
| Ordinal Logistic Regression | [13], [39] |
| Poisson Regression | [40] |
| ANOVA | [41] |
| Triangulation | [11] |
| Pearson Chi-square | [38] |
| Laddering Interviewing Technique | [12], [15], [16], [19], [22], [24], [26], [29], [33] |
| Kendall's Coefficient of Concordance | [17], [18], [20], [23], [28], [31] |

*b) Data collection technique and sample size*: The data collection methods and sample size distributions of the studies are shown in Fig. 5 and Fig. 6, respectively. As shown in Fig. 5, questionnaires are the preferred data collection method in this field of research. A small number of studies used interviews and mixed methods. Focused group discussions and experimental research had relatively limited use in this study field. The distribution of sample sizes in Fig. 6 shows that studies with sample sizes of 201 to 300 people are the most numerous, followed by studies with sample sizes of 301 to 400 and 101 to 200. Studies with sample sizes of 1 to 100 people mainly focused on qualitative research methods, such as interviews and focus group discussions. Studies with sample sizes greater than 600 people are rarer. The authors conclude that the existing research primarily relies on questionnaire-based methods conducted on medium-sized samples.

*c) Profile of respondents*: The characteristics of the respondents are shown in Fig. 7. In these studies, insurance consumers were the most frequently investigated target group, followed by policyholders. Mobile users were also included in some studies. In addition, specific groups such as students, car buyers, university staff, disabled persons, farmers, and athletes were mentioned in a limited number of studies.

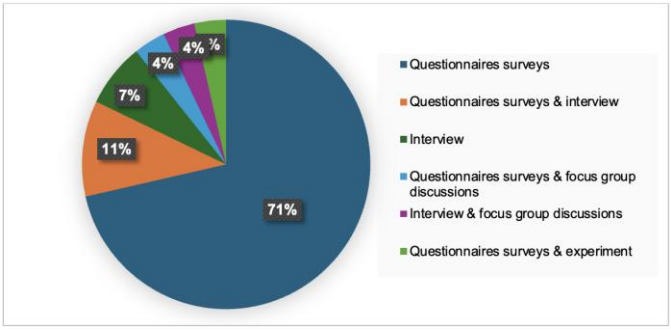


Fig. 5. Data collection method. Source: Compiled by authors

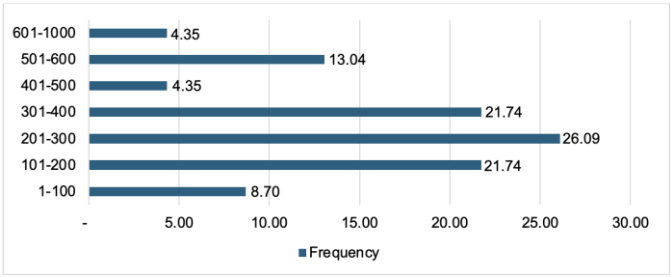


Fig. 6. Sample size used in previous research. Source: Compiled by authors

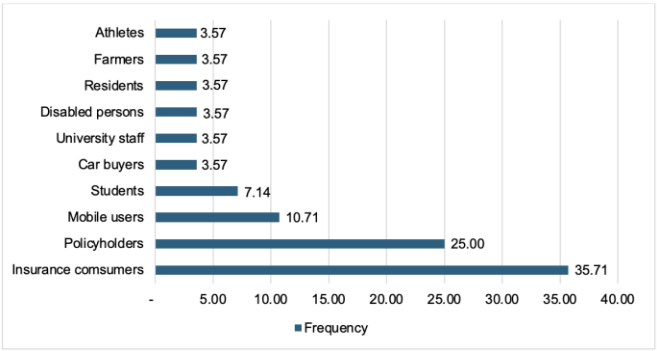


Fig. 7. Profile of respondents. Source: Compiled by authors

*d) Comparison of research methods*: To present the similarities and differences in research methodology of the included literature, 28 studies related to the adoption of digital insurance solutions were categorised. As shown in Table V, the data collection methods, analysis methods and sample characteristics used in each study are summarised.

TABLE V. COMPARISON OF RESEARCH METHODS IN THE REVIEWED LITERATURE

| Authors | Themes of Reviewed Studies | Data Collection Methods | Data Analysis Methods | Respondents and Sample Size |
|---|---|---|---|---|
| Heinze et al. [11] | M-insurance | Interview | Laddering interviewing technique | N=23, Policy holders |
| Gebert-Persson et al. [12] | Online insurance | Interview | SEM | N=322, Insurance consumers |
| Khare et al. [13] | Online insurance | Questionnaire | ANOVA; multiple regression | N=192, Insurance consumers |
| Gowanit et al. [14] | M-insurance | Interview and focused group | N/A | N=177, Insurance consumers |
| Wang and Lu [15] | Online insurance | Questionnaire | SEM | N=270, Insurance consumers |
| Bharti et al. [16] | Insurtech | Questionnaire | PLS-SEM | N=268, Insurance consumers |
| de Andrés-Sánchez and Gené-Albesa [17] | Chatbot-based insurance | Questionnaire | PLS-SEM | N=226, Policy holders |
| de Andrés-Sánchez and Gené-Albesa [18] | Chatbot-based insurance | Interview and questionnaire | PLS-SEM | N=119, University staff |
| de Andrés-Sánchez and Gené-Albesa [19] | Chatbot-based insurance | Questionnaire | SEM | N=226, Policy holders |
| de Andrés-Sánchez and Gené-Albesa [20] | Chatbot-based insurance | Questionnaire | PLS-SEM | N=177, Policy holders |
| Dekkal et al. [21] | Chatbot-based insurance | Questionnaire and experiment | N/A | N=430, Mobile users |
| Huang et al. [22] | Online insurance | Questionnaire | SEM | N=540, Residents |
| Jiang et al. [23] | Online insurance | Questionnaire | PLS-SEM | N=315, Insurance consumers |
| Bromideh [24] | E-insurance | Questionnaire | SEM | N=218, Policy holders |
| Morgan et al. [25] | M-insurance | Questionnaire | Multinomial logistic regression | N=951, Students |
| Toukabri and Ettis [26] | E-Insurance | Questionnaire | SEM | N=280, Policy holders |
| Gupta et al. [27] | Digital insurance | Questionnaire | SEM-ANN | N=323, Disabled persons |
| Hassan et al. [28] | Insurtech | Questionnaire | PLS-SEM | N=350, Insurance consumers |
| Kim and Kim [29] | Digital insurance | Questionnaire | SEM | N=249, Mobile users |
| Milanović et al. [30] | Telematics technology-based insurance | Interview and questionnaire | Multiple regression | N=502, Car buyers |
| Ettis and Haddad [31] | E-insurance | Questionnaire | PLS-SEM | N=200, Insurance consumers |
| Nasrin and Dahana [32] | Online insurance | Questionnaire | Poisson regression; ordinal logistic regression; multinomial logistic regression | N=509, Insurance consumers |
| Luo et al. [33] | Online Insurance | Questionnaire | SEM | N=332, Policy holders |
| Saliba et al. [37] | Wearables-based insurance | Questionnaire | Logistic regression | N=537, Athletes |
| Mensah et al. [38] | Insurance system | Focused group and questionnaire | Multinomial logistic regression; bivariate probit regression; Kendall's coefficient of concordance | N=140, Farmers |
| Nsour et al. [39] | E-insurance | Questionnaire | ANOVA | N=187, Mobile users |
| Salonen et al. [40] | Insurance applications | Interview | Triangulation | N=62, Students |
| Pranav and Dharmalingam [41] | Online insurance | Questionnaire | Pearson Chi- square | N=168, Insurance consumers |

## IV. FINDINGS, DISCUSSIONS, AND FUTURE RESEARCH AGENDA

To answer the first research question (RQ1), we screened 28 empirical studies related to the adoption of digital insurance solutions from the existing literature. The studies are mainly concentrated in Asia and focus on user adoption of e-insurance, mobile insurance, and online insurance. Europe has the second-highest number of studies, focusing on technology-based insurance and user adoption. Unlike Asia, European studies focus more on cutting-edge technologies, such as chatbots, telematics, and wearable devices, suggesting that the European region is more focused on using advanced technologies in the digital insurance industry. In this region, Spain has the highest number of studies, focusing mainly on the practical application of chatbots in insurance. This finding reflects Spain's prominent role in chatbot technology research within the insurance sector. While the number of studies in India and

Spain is comparable, the exploration of insurance digitisation in India is still in the internet-enabled stage.

The second research question (RQ2) was answered using the literature review results. User adoption behavior towards digital insurance solutions is influenced by motivators and inhibitors. Among the motivators, trust, perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, social influence, subjective norms, self-efficacy, system quality, and attitude were mentioned several times as the key drivers of users' willingness to accept the technology. Specifically, users' trust in digital insurance and positive evaluations of the usefulness of service features contribute to the attractiveness of the technology; perceived ease of use and reasonable effort expectancy reduce the psychological burden of using the technology, thus enhancing adoption intentions. In addition, social influences and subjective norms positively shape user perceptions through external pressures or recommendations, self-efficacy enhances user confidence in the use of the technology, and system quality ensures the reliability of the technology. Moreover, positive user attitudes towards digital insurance further drive their willingness to adopt digital solutions.

On the contrary, perceived risk, privacy concerns, perceived complexity, and technology anxiety are the repeatedly mentioned inhibitors to user adoption in existing studies. Users' negative perceptions of digital insurance technologies' potential risks directly reduce their usage willingness. In addition, doubts about privacy security, concerns about technological complexity, and technological anxiety may further increase user resistance and impede the diffusion of digital insurance solutions. These findings highlight the need to focus on and alleviate user concerns, besides enhancing the positive influences when promoting digital insurance technologies.

The authors answered the third research question (RQ3) by sorting the research topic trends, theoretical frameworks, data analysis techniques, data collection methods, and sample distribution. First, all studies were conducted in different contexts of digital insurance solutions, with online insurance being one of the most popular research areas. Although Insurtech and innovation-based insurance are considered future research directions, the number of related studies is relatively small. The authors find that the existing research themes are mainly focused on the application of early digital insurance solutions (e.g., online insurance and mobile insurance). However, with the rapid development of Industry 4.0 technologies, digital insurance has integrated emerging technologies such as blockchain, artificial intelligence, and wearable devices, which offer greater potential for insurance innovation [6]. This scenario indicates that research on digital insurance adoption still has research gaps, especially in the application of cutting-edge insurance technologies and user behavior analysis. Thus, there is an urgent need to explore these areas in depth in future research.

The existing research on digital insurance adoption has relied heavily on classical theoretical frameworks such as TAM, UTAUT, and D&M models, which have broad applicability in explaining user behavior. However, with the evolving technological environment and user needs, classical theories have limitations in explaining complex and dynamic user behaviors. For example, some previously under-attended theoretical frameworks, such as the cognitive-affective-normative (CAN) model, have also been applied to digital insurance-related research [27]. The CAN model provides a multidimensional perspective of users' decisions and behaviors. This suggests that introducing new research variables or developing new framework structures based on existing theories can help explain user behavior in specific contexts.

The commonly used statistical techniques as data analysis tools in existing studies include SEM, PLS-SEM, and logistic regression. SEM is the most popular technique due to its ability to model complex causal relationships, enabling it to offer a significant advantage in the analysis of multivariate interactions [42]. However, these most used methods also have limitations. For example, SEM and PLS-SEM are highly dependent on model assumptions, which may affect the stability of the analysis results when the data quality is insufficient or the sample size is small [43]. Logistic regression has relatively limited performance in dealing with nonlinear relationships and thus may not be able to reveal the interactions between complex variables comprehensively. Based on these limitations, the authors suggest that future research explore emerging analytical techniques to reveal complex indicators and more accurately predict user behaviors.

Questionnaires were the most used instrument for data collection in these studies. The use of questionnaires corresponds to the distribution of research sample sizes, with medium sample sizes of 201 to 400 people being the most common. While studies with small sample sizes were usually conducted using qualitative analysis methods, large sample sizes were less commonly used due to higher resource requirements. It is worth noting that while the findings of insurance consumer and policyholder studies are highly applicable for most user groups, these studies lack in-depth investigations of specific occupational groups (e.g., farmers, athletes) and special populations (e.g., students, disabled people). These limitations may lead to an inadequate understanding of specific groups' behavioral patterns and needs, thus limiting the accuracy of the research results. Therefore, more attention should be paid to the specific groups in the future to explore their unique behavioral patterns and needs in depth.

For the fourth research question (RQ4), the next section provides the answers by discussion of the future research agenda. Applying the TCM framework is comprehensive and instructive, thus providing a clear direction to researchers [44]. The authors propose a future research direction through the TCM framework to bridge the current research gap.

### *A. Future Research Agenda on Theory*

Future research should explore and introduce new theoretical models to better understand the complexity and diversity of the digital insurance sector. Although traditional theories (e.g., TAM and UTAUT) are important in explaining technology adoption behavior, they may be difficult to fully adapt to the contextual needs in the field of digital insurance.

Alternatively, the CAN model provides a comprehensive framework for understanding individuals' intentions to adopt new products; however, it is rarely applied in the insurance industry. Future research could further validate the new model's applicability in the field of digital insurance.

As the insurance industry's digital transformation accelerates, users' perceptions of technology are becoming more complex, and research models need to be more inclusive and multidimensional. Researchers can enrich the explanatory power of existing models by extending the traditional theoretical framework to include insurance industry-specific factors (e.g., insurance literacy, perceived cost, product portfolio, etc.). Also, the key role of inhibiting factors in influencing user behavior should be explored more in future studies. In addition, the authors encourage future scholars to incorporate moderating or mediating factors into the models they develop.

Moreover, future research could integrate interdisciplinary theoretical frameworks, for example, by combining TAM, TPB, UTAUT, and some finance theories. The authors strongly recommend that future research create an Insurtech acceptance model. The interdisciplinary model can cover multiple dimensions, such as technological features, personal psychology, and social environment. Through interdisciplinary integration, digital insurance research will not only provide more accurate behavioral predictions but also offer a more guiding theoretical basis for industry practice by different stakeholders (e.g., policymakers and insurers).

### *B. Future Research Agenda on Context*

Future research should strengthen the studies on specific regions and groups. The existing studies mostly focus on Asian and European regions, leaving less developed regions such as Africa relatively less explored. Due to the low insurance coverage of low-income groups and underdeveloped regions, these groups have become important targets for promoting digital insurance solutions. However, these populations are still understudied in the existing literature in this field. Future research should focus on differences in user acceptance behaviors across cultures (e.g., collectivist and individualist cultures) and social contexts (e.g., rural and urban). An in-depth analysis of these differences will help policymakers and insurers to develop targeted promotional strategies.

In addition, future research should focus on the potential negative impact of digital insurance solutions. Although cutting-edge technologies show great potential in optimising insurance services, research on the related negative effects is still insufficient. For example, while technologies such as blockchain and artificial intelligence enhance transparency and efficiency, risks such as data breaches and algorithmic discrimination may erode users' trust in technologies. Future research should analyse the potential negative antecedents in depth and propose effective countermeasures to optimise user experience and promote a widespread adoption of digital insurance technologies.

Moreover, future research could explore cross-scenario applications of digital insurance solutions, especially by integrating sustainability themes which have received less mention in previous research, such as carbon emission and technology fairness. In addition, future studies are advised to focus on the application of digital insurance in the healthcare industry, an area that is still under-researched. Currently, technologies such as blockchain and artificial intelligence are used for data sharing and health risk assessment in the insurance and healthcare industries [45]. Future research could further explore user acceptance of these technologies.

### *C. Future Research Agenda on Methods*

Future research can employ longitudinal research methods. The promotion of digital insurance and user behavior may be affected by dynamic changes in policies and regulations. Longitudinal studies can reveal the time-series characteristics of behavioral changes by tracking user behavior in stages, such as initial acceptance, continued use, and potential exit [46]. For example, researchers can design multi-year data collection programs that can be used to analyse how policy interventions affect users' willingness to accept digital insurance. However, cross-sectional studies face difficulties to capture these long-term trends and changes. Existing studies on digital insurance are mostly based on cross-sectional analysis; the authors suggest that future researchers explore longitudinal studies more in order to grasp the dynamic changes in consumer behavior.

Another research agenda is to explore the emerging analytical approaches, such as integrating SEM with artificial neural networks (ANN) to cope with the complexity of user behavior studies. Existing analytical methods have limitations in revealing nonlinear relationships, and SEM-ANN approaches can simultaneously leverage the strengths of SEM in causal inference and the capabilities of ANN in nonlinear pattern recognition. For example, SEM-ANN can analyse digital insurance users' willingness to accept at different times and reveal potentially complex behavioral paths. In addition, social network analysis (SNA) is another method worth exploring to reveal users' relationship patterns and behavioral decisions [47].

Future research should also focus on applying machine learning methods in large-scale data processing and behavioral pattern prediction. Machine learning algorithms (e.g., decision trees, random forests, and deep learning) can efficiently process complex user data and mine hidden behavioral patterns from the data [48]. For example, machine learning allows researchers to predict the acceptance willingness of different groups towards digital insurance solutions and identify possible behavioral differences.

## V. CONCLUSION

Digital insurance solutions provide convenient services to people, especially those who have difficulty accessing the insurance market. In the literature analysis, the authors found that digital insurance research themes focused on insurance sector-related technologies in the early digital transformation era, with less exploration on Insurtech, which incorporates emerging technologies. Among the theoretical frameworks, TAM, UTAUT, and D&M models are widely used, but their limitations suggest the need to introduce new theoretical frameworks to explain user behavior more comprehensively. In

terms of research groups, existing studies focused on insurance consumers in general, with a significant lack of research on consumers from low-income groups or less developed regions. The results show that trust, perceived ease of use, perceived usefulness, performance expectancy, effort expectancy, social influence, subjective norms, self-efficacy, system quality, and attitude are the most frequently cited motivational factors. However, the main inhibitors include perceived risk, privacy concerns, perceived complexity, and technology anxiety.

Despite the initial results of this study in identifying the key antecedents influencing the adoption of digital insurance solutions, there are still some methodological limitations. Due to the relatively limited amount of quantifiable data in the existing literature, it is not yet able to perform meta-regression analyses based on multiple studies to systematically validate statistically the relationship between the identified antecedents and adoption. This is mainly since some of the literature adopts qualitative or mixed research methods, and the small number of quantitative studies involved in the antecedent makes it difficult to fulfil the multi-study validation conditions required for meta-analysis. Therefore, the specific impact of the antecedents proposed on the adoption of digital insurance solutions remains to be further verified through empirical data in subsequent studies. Nevertheless, this study provides practical guidance to the government for the promotion of insurance adoption. Additionally, by offering insights into user needs, this study provides strategic recommendations to insurers for enhancing market competitiveness. Academically, this study clarifies the research direction in the field of digital insurance solutions and provides support for subsequent academic exploration.

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# Towards an Optimization Model for Household Waste Bins Location Management

Moulay Lakbir Tahiri Alaoui, Meryam Belhiah, Soumia Ziti
Intelligent Processing and Security of Systems-Faculty of Sciences, Mohammed V University in Rabat, Morocco

***Abstract*—Smart cities require effective, adaptive household waste management systems due to rapid urbanization. Traditional bin placement strategies based on placing bins equidistant among residents fail to account for actual human behavior, leading to overflowing or underused bins. This paper addresses optimizing bin location and capacity through Internet of things (IoT) technologies and data-driven decision-making by deploying LoRaWAN sensors in Tangier City as a case study; real-time usage information was then collected and analyzed. Through statistical analysis and outlier detection techniques, the proposed approach identifies bin placements that are non-optimized by using statistical analysis. It also evaluates data quality and classes bins by their usage level; results show several bins were constantly overused or underused indicating that dynamic placement and capacity adjustment would improve waste collection efficiency, reduce operational costs and enhance citizen satisfaction within a Smart City framework.**

***Keywords*—Smart City; IoT; household waste; LoRaWan; bin location; outlier detection**

## I. Introduction

Cities in developing nations are rapidly expanding, increasing the challenges associated with household waste management. Data collected from networks of IoT sensors placed in waste bins provide valuable data about filling levels and enable dynamic waste collection planning. Leveraging IoT networks to monitor fill rates in real time allows waste collection to be optimized without degrading the quality of service for citizens or wasting resources by emptying half-full bins.

Despite recent advances, several shortcomings remain in existing waste management systems. Many solutions rely on static routing or periodic collection schedules, ignoring real-time variations in bin usage. Prior works often lack robustness against real-world factors such as communication failures, and temporary urban events. To communicate with the servers, some studies use both IOT and GSM [1], which is expensive.

Furthermore, most studies address filling rate without integrating additional factors such as bin moisture and temperature, which are crucial for assessing waste degradation and health risks.

These limitations explain why the problem of dynamic and efficient bin management remains partially unsolved. Existing approaches either oversimplify the complexity of urban environments or fail to incorporate reliable outlier detection, resulting in inefficient resource allocation and increased operational costs [2].

This study proposes a method to optimize bin locations and dimensions based on continuous real-time data collected from sensors embedded in waste bins. The approach also incorporates an optimized routing algorithm for waste collection vehicles, aiming to minimize fuel consumption, travel time, and human resource utilization, which together represent a significant portion of municipal operating budgets [3].

The key contributions of this work are:

- A real-time data analysis framework that integrates fill rate, moisture, and temperature measurements for dynamic waste bin management.
- An outlier detection method designed to distinguish between temporary and permanent bin overflow conditions.
- A system design that considers technical constraints such as energy limitations, frequency interference, and network security in heterogeneous IoT environments.
- An evaluation showing how optimizing bin dimensions and locations can significantly reduce waste management costs.

However, limitations remain. The current system depends on the stability of wireless communication networks and the accuracy of low-cost sensors, which may introduce measurement errors under specific urban conditions.

The remainder of this paper is organized as follows. Section II reviews related works, including the IoT paradigm, IoT network architecture, LoRaWAN technology, and the challenges faced by IoT devices. It also discusses key data quality dimensions and methods to enhance the household waste collection process. Section III presents the proposed optimization model for managing household waste bin locations, including the outlier detection method, comparison metrics, and hyperparameter tuning process. It also describes the case study conducted in Tangier City, detailing data pre-analysis, quality verification, and outlier detection results. Section IV presents and discusses the results, including data pre-analysis, quality verification, outlier detection, and identification of slow- and fast-filling bins. Section V concludes the paper and suggests future research directions.

## II. Related Works

### A. IoT Paradigm

IoT and internet of everything (IoE) refer to a connected world where all objects are interconnected via ubiquitous sensors [4] and devices from different manufacturer's need to

exchange data. The IoT economic impact could grow to $3,352.97 billion by 2030 [5] ; the number of IoT devices may reach 75 billion [6].

Globally dispersed, diverse, and heterogeneous IoT devices provide data that influence interoperability and data quality [6].

Heterogeneous networks and sensors' challenges are the origin of communication problems between multiple nodes and layers. The following sub-chapter delves into the fundamental structure, components, and layers of IoT, exploring their applications and challenges.

### B. IoT Network Architecture

The IoT architecture is divided into several layers [7], each one responsible for different functions within the ecosystem as depicted in Fig. 1:

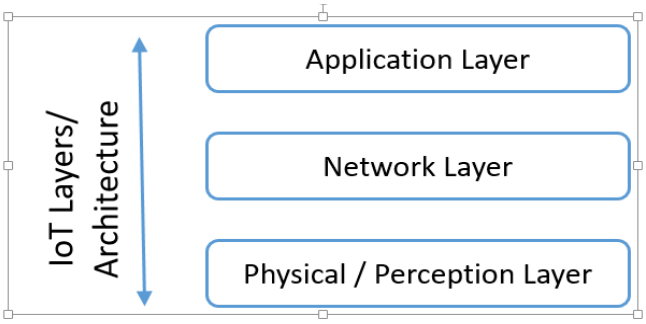



Fig. 1. IoT Architectre [7].

The physical layer, sometimes referred to as the perception layer, is in charge of actuating the environment in real time, measurement, and communication to the next layer, like temperature, bin level filling, moisture, geolocation, etc.

Maintenance of these devices poses challenges in terms of replacement and repair due to potential sensor placement in inconvenient locations [8]. This could lead to operational difficulties and even delays in data collection. Moreover, environmental conditions like high temperatures or humidity can affect sensor performance, necessitating extra care during hardware maintenance procedures. Furthermore, issues with the power supply or connectivity may make it difficult for the physical layer sensors to function. It may be necessary to regularly monitor and troubleshoot these issues in order to ensure accurate and uninterrupted data transmission. Defective equipment can lead to a malfunctioning sensor that produces inaccurate data, affecting service delivery and overall business insights.

Sensors often face limitations: being cost-effective means they aren't of the highest quality and have limited capacities. This includes issues with connectivity and short battery life for various functions, lack of precision, loss of calibration, and keeping up reporting once the device becomes faulty [9].

Noise is a major problem for sensors. The signals they rely on can be seriously disrupted by interference or physical impediments, which results in inaccurate data collection[10].

Network layer: interconnects IoT devices with the next layer [11] using universal protocols.

Application layer: controls sensors, receives data, analyzes them, and takes decisions[12].

In the next subsection, we describe the LoRaWan solution and present its benefits and drawbacks.

### C. LoRaWan

LoRaWan is a member of the Low Power Wide Area Network (LPWAN) family. These devices use the medium access control protocol (MAC) mechanism to communicate with the gateway.

*1) LoRaWAN Dataframe:* Dataframes have the same time duration. To overcome noise and interference, LoRa uses forward error correction (FEC) codes ranging between 4/8 and 4/5 and diagonal interleaving. The symbol rate Sr depends on the bandwith Bw and the spreading factor according to the Formula (1) [13]:

$$S_r = \frac{Sp * B_w}{2^{SF}} \quad (1)$$

*2) LoRaWAN Topology:* LoRaWan has a star topology as per Fig. 2 [14]. Sensors can only communicate with the gateways but not with each other; gateways communicate with the server; they encapsulate raw data received from sensors in UDP/IP packets and send them to the server. The server sends downlink packets and commands. Devices are divided into three classes [15]:

Class A: has basic options needed to join a LoRaWan network. Bidirectional communication can be enabled. Class A devices are most of the time asleep, thus they consume the least of power.

Class B: more receive windows can be scheduled to get synchronized and to inform when devices are ready for downlink traffic; power consumption is higher than the first ones.

Class C: Receive windows are open continuously except during transmission, power consumption is higher for this class.

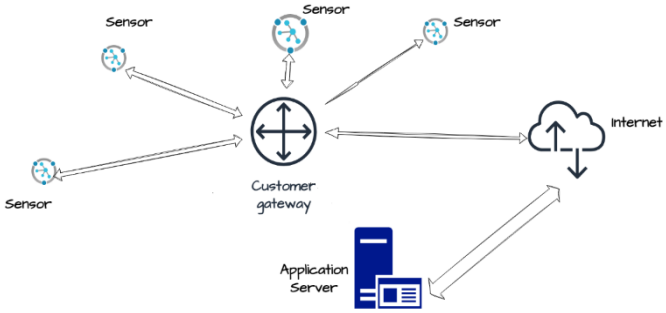



Fig. 2. LoRaWan network topology.

*3) LoRaWAN transmission:* The LoRa physical layer can use 125 KHz channels from the bands 433 MHz, 868 MHz, and 915 MHz to transmit, sensors communicate within 1% of the time only and transmit a small amount of data [16].

To guarantee secure and reliable communication, LoRaWan sets a number of mechanisms and joining procedures for sensors.

Once the sensor joins the network and is activated using over-the-air procedure (OTAA) [17] or by personalization (ABP) [18], the device sends a join or re-join message with needed keys and identifiers and gets a join-accept message from the server. The use of open source protocols helps to reduce the solution fees; the communication protocol MAC [19] is used between the sensors and the gateway; furthermore, to avoid financing frequency license fees, unlicensed bands may be used; the 868 MHz sub-band is unlicensed in Europe [20] and Morocco, according to the frequency regulation center [21].

Numerous technologies, including SigFox, IEEE 802.15.4g, LoRaWAN, and Z-Wave, use the same frequency, which may have an effect on signal quality and interference. In order to overcome interference, European regulations share time resources; a radio transmitting for one second cannot transmit for the next 99 seconds [22].

### D. LoRaWan Solution to IoT Devices Challenges

With the cited information above, the LoRaWan solution overcomes most of the IoT constraints while maintaining the same quality of service:

- *Joining and re-joining procedures:* restrict the sensors allowed to send data to MGWs.
- *Power consumption*: LoRaWan is a low-power area network [15]; sensors are asleep most of the time, especially for class A devices. Sensors contain a solar panel that extends the lifespan of sensor batteries and delivers sufficient voltage to sensor units (low power transmitter). Fig. 3 shows LoraWan Sensor modules. The embedded GPS module in the device helps to inform trucks about exact geolocation and to identify the location of bins. Table I summarizes solutions to most sensor challenges and the reason behind the popularity of this technology.
- Frequency transmission fees: as per [16] free of charge frequency usage to reduce the solution cost.
- Interference using processes like listen before sending or sending 1% of the time reduces considerably the interference. Data control and preprocessing can be done on the application server.
- Distance between the sensors and the gateway can reach 6 km with a high reception rate (more than 90%) [23].
- Synchronization: Is a drawback for LoRaWan [24]
- Access to transmission channels from multiple and heterogeneous sensors is unpredictable which causes collision and loss of frames [25].

TABLE I. LORAWAN SOLUTION TO IOT DEVICES CHALLENGES

| Challenge | Solution | Details |
|---|---|---|
| Power consumption | Low power consumption | Sensors are asleep most of the time |
| Frequency transmission fees | Free of charge frequency usage | Used to reduce charges |
| Interference | Sending 1% of the time reduces considerably the interference | A limited number of devices can transmit in the same time |

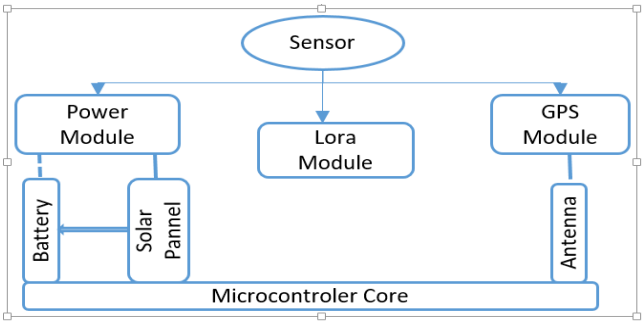



Fig. 3. LoRaWan sensor modules.

In the following section, we will present the most important dimensions regarding data quality.

### E. Data Quality Dimensions

Data dimensions are characteristics of data quality that can reveal the data's overall quality level once they are measured correctly [26]. Data quality is a crucial parameter for services based on IoT; a control and validation of the quality are mandatory before model deployment. Herein we will define the most influencing data quality dimensions:

*1) Accuracy:* Evaluates the reliability, dependability, and certification of data [27]. It represents the degree to which observations are correct, trustworthy, and guaranteed error-free. It can also be defined as how a value 'v' is close to the correct value of the real world.

*2) Completeness:* A «NULL» value may indicate a missing value, which is an existing value in the real world but the observation is lost for a specified reason; those values may exist but are unknown, or they do not exist, or the system does not know if they exist or not [28].

*3) Timeliness, volatility and currency:* The temporal dimensions are sensitive since late data may be unuseful. Timeliness describes how current the data are; it can alternatively be described as the offset between the server time and the received sensor's timestamp. Volatility is a measure of how frequently data changes over time; where currency specifies how fast data are updated, it can be defined as in Formula (2) [29]:

$$\text{Currency} = \text{Age} + (\text{Delivery\_Time} - \text{Input\_Time}) \quad (2)$$

where, "age" indicates the data's original age upon receipt and "Input_time" is the server time when data are observed.

### F. Household Waste Collection Process Enhancement

While the majority of research concentrated on management and trash classification, the current work looks at bin locations and identifies inadequate ones; it also shows outliers, including the most and least used bins; as well as inaccurate data produced by malfunctioning devices. Non-synchronized bins are sorted out to permit a full operational waste collection process. The data control part in our program can be deployed by other IoT services.

## III. Towards an Optimization Model for Household Waste Bins Location Management

### A. Outlier Detection Model Presentation

Outliers represent a rare event in a dataset; this unexpected value may be due to a measurement error or a faulty sensor, but it can also be a valuable insight [27]. In this subsection, we will present the main steps and procedures of our model that detects outliers. Data may be numbers, dates, geo-location values, etc.

Our model is built using Jupyter Notebook with required libraries and dependencies installed, like Pandas, Numpy, Matplotlib, Sickit-Learn, Pyod, Pycaret etc. The model is designed to operate in a variety of fields; it can be adapted according to each domain specification, and the following steps are performed:

- Data collection: supplied data, in text, csv, or other formats, contain multiple columns; it is filtered to keep necessary columns for our model.
- Cleanup: NaN and empty values represent a non-complete observation; it should be detected and cleaned/corrected.
- Preprocessing: data columns are interpreted as object types and need to be converted to appropriate types such as date time, integer, etc.
- Data normalization and feature selection: features should have similar scales with a low correlation level to provide better results. The data show below variables:
  - The server time (servertime) and time of the IoT device related to the observation.
  - Bin_number, Bin_index1 and Bin_index2 represent an identyer of the waste bin used by different layers.
  - Filling_level is a variable measuring the fill level of a Bin.
  - Bin_longitude and latitude represents GPS coordinates.

Time identifiers and Bin indexes are correlated as per Fig. 4. To detect outliers we use the variables bin identifier, time and fill level etc. A new variable will be introduced to classify data per day of the year.

- Data from Bin_index columns are converted to a dictionary to simplify data analysis and allow exploration of data through outlier detection methods requiring numerical values.
- Parameter tuning: we can change the ratio of data to train the model according to the data size, and other parameters can be changed according to our need.
- Pandas library helps to sort out IoT devices that overflow the server and bins rarely transmitting their filling level. We use Pycaret to detect outliers, tune, and compare the models.
- Model comparison: different outlier detection models can be compared using different metrics, as we will present in the next subsection.

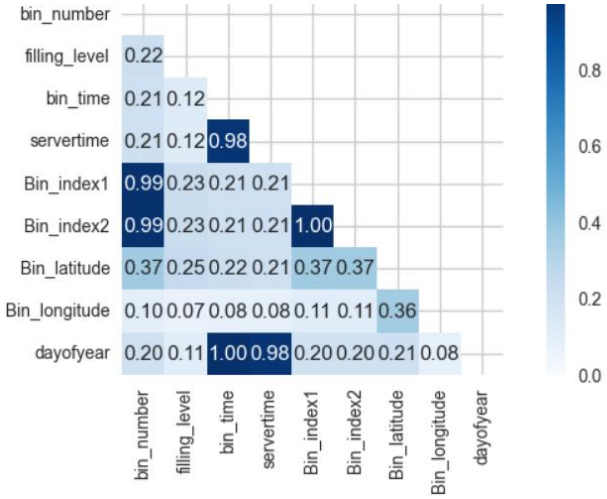



Fig. 4. Correlation matrix.

The Fig. 5 below summarizes different data treatment steps of our program:

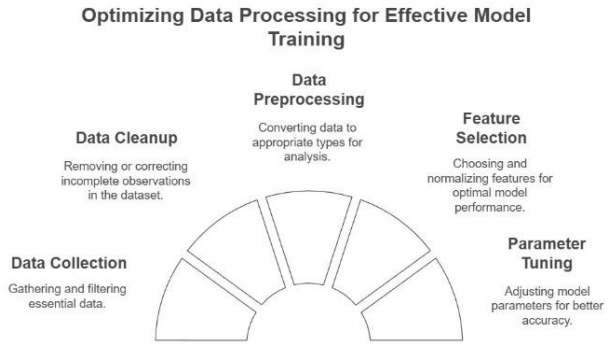



Fig. 5. Data processing.

*1) Comparison metrics:* The model sorts out the best method to detect outliers based on the best metrics. The main metrics used in the case of classification models are [30]:

- Accuracy: it presents the ratio of the correct prediction numbers to all the prediction numbers.

$$\text{Accuracy} = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (3)$$

$$\text{Auc} = \frac{1 + Correct\ positif\ predicts - Incorrect\ positif\ predict}{2} \quad (4)$$

$$\text{Recall:}\quad \text{Recall} = \frac{Correct\ positif}{Correct\ positif + False\ negatif} \quad (5)$$

$$\text{Precision:}\quad \text{Precision} = \frac{Correct\ positif\ results}{Correct + False\ positif\ results} \quad (6)$$

$$\text{F1 Score:}\quad \text{F1} = 2 * \frac{Precision * Recall}{Precision + Recall} \quad [31] \quad (7)$$

*2) Outlier detection using KNN method:* The number of neighbors to be given an integer K, this method calculates the distance to the k nearest neighbors. In a m-dimentional space,

let A and B be two points; they can be expressed as the tulpes: (A[1], A[2],…A[m]) and (B[1], B[2]…B[m]). The distance AB can be : $\sqrt{(\sum(B[i]-A[i])2}$. An object O is an outlier if the number of neighbors within a distance r defined as a threshold is less than K.

To detect outliers, we use Pycaret 3.3.1. Setup function trains the environment, multiple parameters can be specified in this step such us features, thresholds, outlier method, the number of neighbors to be used for KNN method, etc. possible models can be listed, compared, and the best model is identified, the model is tuned and saved for future use.

*3) Hyperparameter tuning:* Finding outliers is not an easy task; it depends on many factors. The model should be well trained, which requires a large dataset with low-correlated features. It also depends on how rare the outliers we are interested in are. Using default parameter values for a model helps to sort out data that are very different; however, to detect outliers that are not completely different, parameter tuning is mandatory [32]. The number of neighbors can be increased and the threshold reduced. The number of dimensions may be large, which increases computational resources and time. Principal Component Analysis (PCA) is used to overcome this issue and convert correlated variables to non-correlated ones.

### *B. Case Study: Household Collection in Tangier City*

This study concerns a part of the Tangier city, one of the biggest cities in northern Morocco; it has undergone an economic and demographic surge empowered by the establishment of the Tangier-Med port, cars and aircraft manufacturers, among other development factors. Like many growing cities, the population has risen significantly; therefore, public services have to follow the pace.

In most cities, household waste collection is planned once a day in low traffic periods. Although this approach appears to be effective, it has a number of drawbacks, and there is more to be done to optimize the collection process. Indeed, time, fuel consumption, and human resources will be overused if we include the total number of bins in everyday travel in order to empty and clean them up.

## IV. RESULTS

This paper aims to sort out the rate at which bins are filling up. Datas are gathered from different LoRaWan sensors placed in all household bins in the studied region.

Data is collected over a 10-day period, sensors calculate bins filling level and send it to a central server, where, GPS location (longitude and latitude), server time, and measurement time are included. It is important to highlight data quality efforts provided in different layers in the network.

### *A. Data Pre-analyzis and Data Quality Check*

*1) Accuracy:* To monitor bin filling level, gathered data from different sensors should be reliable. A sensor hardware or software failure may cause a reduced number of observations or may flood the system with observation signals. Table II shows such abnormal behavior from sensors that need to be checked. The column “Bin Number” is an identifier of bins; “Num of measurements during 10 days” represents the sum of observations during the supervision period, while the other columns show the number of observations for each day of the year (194 refers to 13th July, 195 to 14th July..).

*2) Completeness:* The server discards incomplete frames and missing values; incomplete ones will lead to a « Null » value that will be discarded in our data pre-treatment program.

*3) Timeliness:* Data age is an essential parameter; old data do not reflect reality and cannot be used to make a decision. The time difference between the server and sensors data measurement can indicate rows to exclude from data analysis; this offset will be considered in our program.

- Bins 495 and 529 sent 60982 messages during the ten days.
- Bin 529 sent 33959 during the ten days (33506 during 3 days).
- Bin 495 sent 27007 during 3 days.
- Bins 266, 271, 20, 274, and 274 sent 2 messages each during the whole ten days. Other indicators may help to find faulty devices: 391 reported only 8 measurement values during the 10 days and passed from 10% to 100% within 12 seconds between 2024-07-20 08:58:53 and 2024-07-20 08:59:05.

A normal bin’s data are also included; « bin 28 » sent 1102 observations well spread over the monitored period, with different filling level values; those observations were continually sent to the server, with a minimum of 58 and a maximum of 143 observations per day.

### *B. Outlier Detection*

In this subsection, we will present the result of the computational program that aims to sort out outliers that need to be analyzed and take actions accordingly. Python with machine learning libraries such us Sickit Learn, Pandas, Matplotlib, and PyOD are used to develop our computation software. After data cleanup, training, testing, and evaluation, our model detects outliers. KNN is used since it has the best performing metrics: accuracy, recall, F1-score, and precision, as it is highlighted in Table III.

Found outliers contain a few bins that are 100% filled up and that are mentioned in the above subsections (bin numbers: 121, 516, 304, 503, 200, and 352). Other bins need to be highlighted and studied (bin numbers: 312, 2, 494, 452, 511, 201, 465, 376, 208, 536, 539, 545, 547, 518, 13) as per Fig. 6. More investigations need to be done to check why each of those locations represents an outlier and different stakeholders have to be involved to take a decision according to the analysis results. Other outlier methods with parameter tuning need to be used for more accurate data analysis.

TABLE II. NUMBER OF MEASUREMENTS PER SENSOR DURING THE SUPERVISION PERIOD

| Bin Number | Number of measurements during 10 days | Day of the year | 195 | 196 | 197 | 198 | 199 | 200 | 201 | 202 | 203 | 204 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 194 | | | | | | | | | | |
| Bin_Number_352 | 8402 | 6 | 2 | 4 | 2 | 1099 | 2658 | 0 | 0 | 1653 | 0 | 2978 |
| Bin_Number_495 | 27023 | 6 | 2 | 4 | 2 | 4015 | 9831 | 13161 | 0 | 0 | 0 | 2 |
| Bin_Number_529 | 33959 | 6 | 2 | 4 | 2 | 439 | 0 | 0 | 0 | 9978 | 11937 | 11591 |
| Bin_Number_266 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_271 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_20 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_274 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_273 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_391 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 0 | 2 |
| Bin_Number_307 | 16 | 6 | 2 | 4 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_42 | 16 | 6 | 2 | 4 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_198 | 16 | 6 | 2 | 4 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_219 | 16 | 6 | 2 | 4 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_435 | 16 | 6 | 2 | 4 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Bin_Number_414 | 20 | 6 | 2 | 4 | 2 | 0 | 0 | 0 | 0 | 4 | 0 | 2 |
| Bin_Number_28 | 1102 | 72 | 75 | 114 | 104 | 116 | 143 | 124 | 108 | 92 | 96 | 58 |

TABLE III. BEST PERFORMING OUTLIER DETECTION ALGORITHMS

| Model | | Accuracy(3) | AUC(4) | Recall(5) | Prec.(6) | F1(7) | Kappa | MCC | TT (Sec) |
|---|---|---|---|---|---|---|---|---|---|
| **knn** | K Neighbors Classifier | 0.3516 | 0.7917 | 0.3516 | 0.3441 | 0.342 | 0.3263 | 0.327 | 8.58 |
| **nb** | Naive Bayes | 0.2339 | 0.7486 | 0.2339 | 0.1494 | 0.174 | 0.1905 | 0.196 | 4.027 |
| **dummy** | Dummy Classifier | 0.108 | 0.5 | 0.108 | 0.0117 | 0.021 | 0 | 0 | 2.499 |
| **svm** | SVM - Linear Kernel | 0.0826 | 0 | 0.0826 | 0.1335 | 0.077 | 0.0697 | 0.102 | 787.618 |
| **qda** | Quadratic Discriminant Analysis | 0.0087 | 0 | 0.0087 | 0.001 | 0.0210 | 0 | 0 | 4.073 |

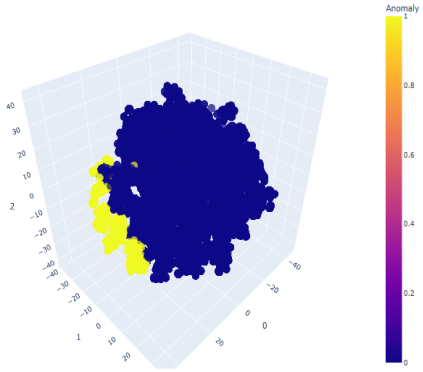



Fig. 6. Outlier bins pertaining to fill level.

The outlier detection can be used as a first step; more analysis follow to check the reasons behind those bins to be outliers. Checking outliers reduces computational resources and filters bins and sensors to monitor.

### C. Slowest Filling Up Bins

Bins that fill up slowly can be deprioritized during waste collection. Unnecessary travels to those bins can be avoided.

Table IV shows multiple bins that did not exceed 30% of their capacity during 2024-07-12. These bins do not require immediate emptying and can be excluded from daily routes. During this day Bin_451 and Bin_225 recorded a 0% fill level, Bin_456, Bin_151, and Bin_44 stayed below 10% and most bins listed remained under 25%.

Table V highlights bins that remained underused over a 10-day period. Specifically, it shows the number of days during which each bin did not reach a 50% fill level.

Bin_Number_44 never reached half capacity during the entire 10-day period, Bin_Number_533, 532, 310, and 120 exceeded 50% capacity only once. Several other bins stayed below the threshold for 6 or 7 days.

Concerned bin sizes and places should be reviewed.

Table VI presents the maximum daily fill levels recorded for Bin_Number_514 over an 11-day supervision period. During 6 of these 11 days, the bin did not exceed the 50% fill threshold. Only between Days 201 and 203 did the fill level rise above 60%, with a peak of 74%. On Day 204, the fill level dropped sharply to 22%, reflecting a possible irregular usage pattern or external intervention such as manual emptying.

TABLE IV. BINS NOT REACHING 30% FILL-UP LEVEL ON 2024-07-12

| bin_num | max_fill up level | bin_num | max_fill up level | bin_num | maxfill_up level | bin_num | max_fill up level |
|---|---|---|---|---|---|---|---|
| Bin_451 | 0 | Bin_412 | 17 | Bin_395 | 22 | Bin_382 | 24 |
| Bin_225 | 0 | Bin_532 | 20 | Bin_533 | 22 | Bin_365 | 24 |
| Bin_456 | 2 | Bin_495 | 20 | Bin_493 | 22 | Bin_524 | 25 |
| Bin_151 | 3 | Bin_224 | 21 | Bin_217 | 23 | Bin_479 | 25 |
| Bin_44 | 9 | Bin_386 | 21 | Bin_508 | 23 | Bin_355 | 25 |
| Bin_204 | 10 | Bin_363 | 21 | Bin_481 | 23 | Bin_360 | 25 |
| Bin_467 | 11 | Bin_380 | 21 | Bin_34 | 23 | Bin_417 | 25 |
| Bin_215 | 11 | Bin_188 | 21 | Bin_414 | 24 | Bin_369 | 25 |
| Bin_405 | 14 | Bin_316 | 21 | Bin_529 | 24 | Bin_361 | 26 |
| Bin_69 | 16 | Bin_498 | 21 | Bin_388 | 24 | Bin_120 | 27 |
| Bin_439 | 17 | Bin_368 | 22 | Bin_497 | 24 | Bin_375 | 29 |

TABLE V. NUMBER OF DAYS /10 THE MAXIMUM FILL LEVEL DID NOT REACH 50%

| Bin Number | N of occurrences | Bin Number | N of occurrences |
|---|---|---|---|
| 44 | 10 | 343 | 7 |
| 533 | 9 | 515 | 7 |
| 532 | 9 | 350 | 7 |
| 310 | 9 | 412 | 7 |
| 120 | 9 | 40 | 7 |
| 488 | 8 | 417 | 6 |
| 506 | 8 | 182 | 6 |
| 535 | 7 | 456 | 6 |
| 467 | 7 | 514 | 6 |

Fig. 7 illustrates the fill level evolution for Bin N44, N532, and N533 over the supervision period. These bins display consistently low filling patterns. Although short spikes are observed, the majority of values remain below the 50% threshold. Bin N44, for instance, shows extended periods near zero. Bin N532 briefly exceeds 60%, then stabilizes below 30%. Bin N533 presents a single peak but quickly returns to lower levels. These trends confirm the underuse highlighted in Table V. They suggest that these bins may not require daily collection. However, the accuracy of the recorded values must be verified before operational adjustments are made.

The map below (Fig. 8) shows the geospatial distribution of bins that consistently reported low fill levels during the 10-day monitoring period in the city of Tangier. These bins, highlighted on the map, rarely exceeded 50% capacity.

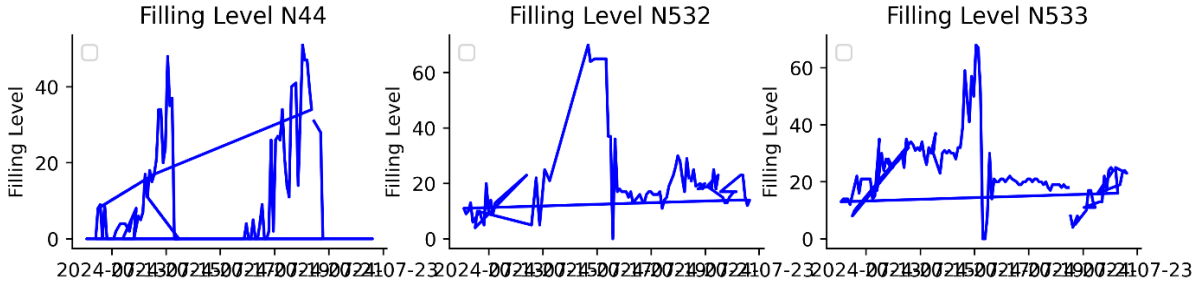



Fig. 7. Bins with a low filling level during the supervision period.

TABLE VI. MAXIMUM FILL LEVEL DURING SUPERVISION PERIOD FOR N514

| day | Bin Num | level | newla | newlo | date | time |
|---|---|---|---|---|---|---|
| 194 | 514 | 34 | 35.767506 | -5.800178 | 12/07/2024 | 21:06:47 |
| 195 | 514 | 37 | 35.767506 | -5.800178 | 13/07/2024 | 23:30:21 |
| 196 | 514 | 37 | 35.767506 | -5.800178 | 14/07/2024 | 21:04:33 |
| 197 | 514 | 54 | 35.767506 | -5.800178 | 15/07/2024 | 19:19:16 |
| 198 | 514 | 52 | 35.767506 | -5.800178 | 16/07/2024 | 21:10:16 |
| 199 | 514 | 48 | 35.767506 | -5.800178 | 17/07/2024 | 21:02:31 |
| 200 | 514 | 40 | 35.767506 | -5.800178 | 18/07/2024 | 18:56:37 |
| 201 | 514 | 64 | 35.767506 | -5.800178 | 19/07/2024 | 18:49:52 |
| 202 | 514 | 68 | 35.767506 | -5.800178 | 20/07/2024 | 18:42:25 |
| 203 | 514 | 74 | 35.767506 | -5.800178 | 21/07/2024 | 12:36:42 |
| 204 | 514 | 22 | 35.767506 | -5.800178 | 22/07/2024 | 13:50:17 |

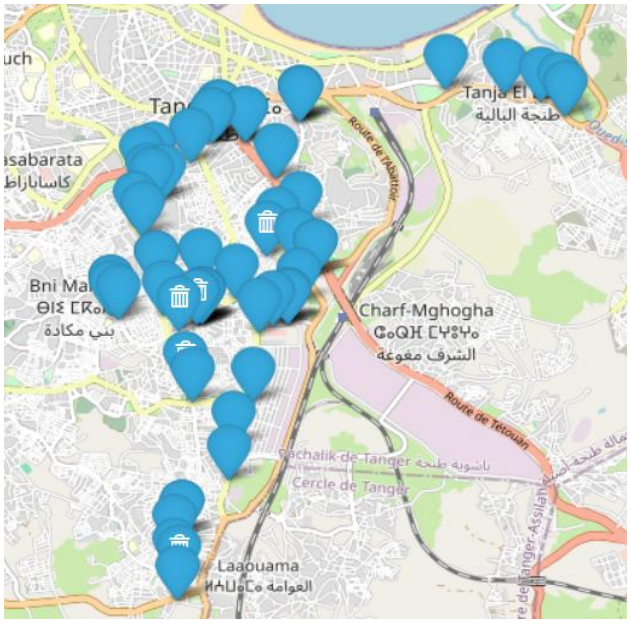
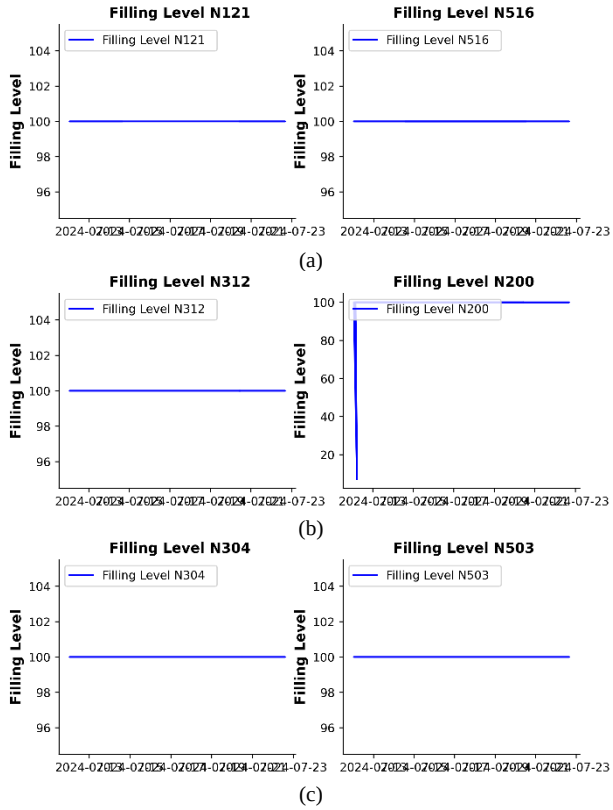



Fig. 8. Bins with a low filling level during the supervision period.

## D. Fastest Filling up Bins

A filled-up bin can emit an unpleasant odor, which impacts the life quality of citizens. In this subsection, we will sort out the fastest-filling bins.




(a)

(b)

(c)

Fig. 9. (a) Bins with abnormal filling level for N121 and N516, (b) Bins with abnormal filling level for N121 and N516, (c) Bins with abnormal filling level for N304 and N503.

Data analysis indicates the following results: Bins 121, 516, 304, 503, 200, and 352, exhibited a constant filling level of 100% throughout the supervision period, following a small number of initial readings below that threshold. For example, Bin 352 recorded only 14 initial values below 100%, followed by 8,388 consecutive values at 100% as per Fig. 9(a), 9(b), and 9(c) which indicates a device failure that needs to be fixed.

The list below presents the quickest filled up bins; Fig. 10 shows their geolocations; those bins should be replaced with bins having a bigger capacity to answer citizens demand: [bin numbers: '121', '516', '312', '200', '304', '2', '503', '494', '452', '511', '201', '465', '376', '208', '536', '539', '545', '547', '518', '13', '541', '542'].

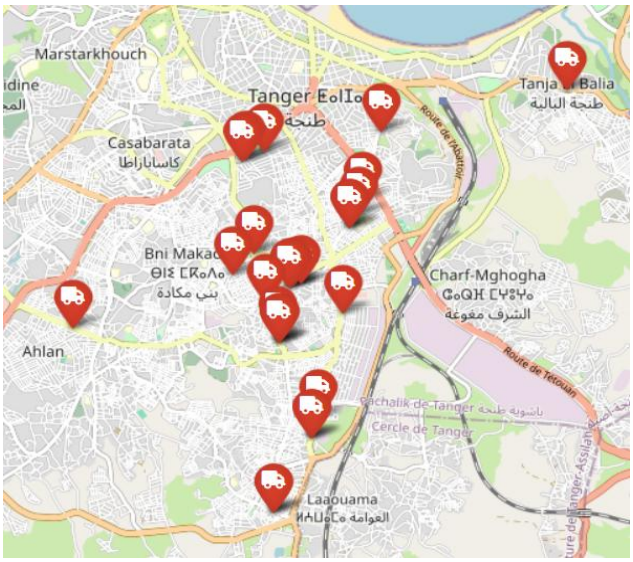



Fig. 10. Bins with a high filling level during the supervision period.

The map below combines both types of bins Fig. 11.

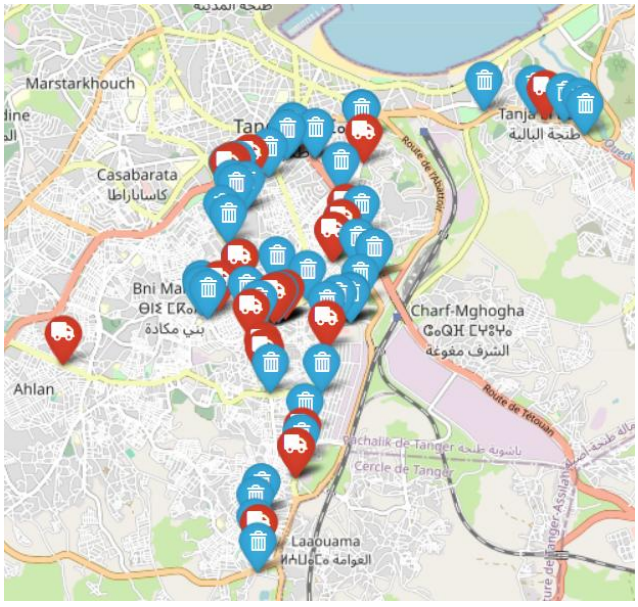



Fig. 11. Bins with a high filling level and the ones with a low filling level.

Fig. 11 presents a combined geospatial representation of waste bins with contrasting usage patterns during the supervision period. Red markers indicate bins with consistently high fill levels, while blue markers represent underused bins with persistently low fill levels.

This dual-layered view enables rapid identification of mismatches between bin capacity and local waste generation dynamics. High-fill bins highlight priority zones for:

- Capacity increase
- Additional bin deployment
- More frequent collection schedules

Low-fill bins suggest potential for:

- Relocation
- Downsizing
- Reduced collection frequency

Such spatial insights are essential for optimizing operational efficiency, minimizing collection costs, and maintaining service quality across the city. Nevertheless, sensor reliability must be verified before implementing adjustments to avoid decisions based on inaccurate data.

### *E. Discussion*

Provided data offers valuable insights about the functional state of LoRaWan sensors, indeed:

- Several IoT-based technologies communicate filling levels via GSM texting. The expense of communication is therefore unsustainable. In just 10 days, Bin_Number_529 sent 33,959 messages. The GSM [1]method is very costly because, at 0.05 USD each SMS, for instance, that amounts to 1,697.95 USD for a single bin. Over the course of 10 days, bins 529, 495, and 352 sent 69384 messages. Scaled to a citywide network, the cost becomes huge, the proposed solution is performing better than [1] and [33] using GSM especially that LoRaWan uses free transmission band.
- Synchronization state of sensors: the dataset shows a big time offset between the server and sensors clock which may lead to incorrect observation.
- Unreliable information as demonstrate by bins 121, 516, and 352 in Fig. 9(a), Fig. 9(b) which were 100% filled up throughout the duration or a brutal filling level from 10 to 100% within 12 seconds. Fig. 9(b) indicating a faulty measure or faulty device: such behavior indicates a faulty device which facilitate the maintenance process.
- An erroneous GPS location of a sensor indicates a displacement of the bin or a faulty device measurement, which allows tracking bins in real time.
- Data control helps to maintain sensors in a healthy state and keeps transmitted data frames accurate. Maintaining IOT devices is easier by measuring data quality and avoiding traffic outage. Suspected faulty devices should be checked which allows a continuous bin fill level check.
- Truck trips can be significantly reduced by avoiding travels to bins not reaching a predefined filling threshold level; this impacts also travel time and man hours; fuel consumption and its impact on the environment can be reduced; more than that, transportation trucks can be reused and their number reduced.
- Hot seasons and special events are another critical context where waste collection efficiency directly impacts service quality and citizen satisfaction. During these periods, waste generation increases rapidly, and delayed responses can degrade urban hygiene and public perception. Monitoring the fill level of all bins in real time, while ensuring data quality, enables timely emptying of full bins. This optimizes collection routes, avoids emptying bins that are not yet full, and reduces unnecessary trips, fuel consumption, and human resource usage.

Supervising the filling level of bins for long periods indicates less used ones; a rarely used bin does not have to be emptied on a daily basis, which minimizes resource usage. The above-listed bin geolocations mentioned in the previous subsection should be reviewed; indeed, it can be displaced to more demanded locations.

On the other hand, dimensions of bins with a high level of fill-up should be resized; bigger bin sizes are needed to answer citizens' demand. Above parameters, among others, are keys of bin geolocation optimization.

There is a limitation to this study in receiving data; indeed, the analysis is impossible without valid and accurate data.

## V. CONCLUSION

This study has enabled us to implement a program that controls IoT data quality, especially the most important dimensions such as timeliness, completeness, and accuracy.

By processing observations collected by the various devices, a full operational IoT network is maintained by early detecting faulty devices. It is possible to reduce the distance covered by bin collection trucks and reduce collection time, as well as fuel consumption and its impact on the environment.

As the location of bins is a key element in the service provided to citizens, this program allows to detect locations that are underused and that need to be displaced to a more demanded area; it also detects bins that are frequently overloaded and for which the size needs to be increased or enhances the emptying frequency, especially in hot seasons or during special events where the demand increases substantially and the service quality KPIs should be higher.

To optimize bin geolocation positions, long-term supervision needs to be put in place. Outlier method results can sort out locations that need to be highlighted. Deeper investigations regarding each outlier needed to be performed to take actions, by either increasing the bin's size, displacing the bin, or keeping the bin under surveillance.

This study focused on optimizing household waste collections based on real-time sensor data and bin usage patterns. Future work will focus on automating recycling integration at waste deposit points.

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# Enhancing Electric Vehicle Security with Face Recognition: Implementation Using Raspberry Pi

Jamil Abedalrahim Jamil Alsayaydeh[1]*, Chin Wei Yi[2], Rex Bacarra[3],
Fatimah Abdulridha Rashid[4], Safarudin Gazali Herawan[5]
Department of Engineering Technology-Fakulti Teknologi Dan Kejuruteraan Elektronik Dan Komputer (FTKEK),
Universiti Teknikal Malaysia Melaka (UTeM), 76100 Melaka, Malaysia[1, 2]
Department of Computer Engineering, University of Al-Iraqia, Baghdad, Iraq[4]
Department of General Education and Foundation, Rabdan Academy, Abu Dhabi, United Arab Emirates[3]
Industrial Engineering Department-Faculty of Engineering, Bina Nusantara University, Jakarta, Indonesia 11480[5]

***Abstract*—Facial identification has emerged as a key research area due to its potential to enhance biometric security. This research proposes an advanced security system for electric vehicles (EVs) based on facial identification, implemented using Raspberry Pi. The system comprises two main modules: Face Detection and Face Recognition. For face detection, the researchers propose using the Viola-Jones algorithm, which leverages Haar-like features to detect and extract unique facial features, such as the eyes, nose, and mouth. MATLAB will be used as the development tool for this module. For face recognition, the proposed approach integrates Principal Component Analysis (PCA) with Support Vector Machine (SVM). PCA is used to extract the most relevant facial information and construct a computational model, while SVM enhances classification accuracy. The system's performance is evaluated using accuracy and the Receiver Operating Characteristic (ROC) curve, with results demonstrating a face recognition accuracy of 95% and an average execution time of 2.32 seconds, meeting real-time operational requirements. These findings confirm the proposed method's reliability in offering advanced and efficient biometric protection for modern electric vehicles.**

***Keywords*—Face recognition; face detection; Principal Component Analysis (PCA); Support Vector Machine (SVM); Raspberry Pi***

## I. INTRODUCTION

In this era of globalization, the rapid growth of modern electrical vehicles (EV) with advanced technologies requires strong security to prevent customer's vehicle begin stolen. Passive Entry Passive Start (PEPS) was introduced to enhance the security of EV by using low-frequency (typically 125 kHz) or ultra-high-frequency signals to exchange unique key access codes between the key and the vehicle. When these codes match and yield the expected value, and the key is within the vehicle's range, the car grants access to the driver [1], [2].

However, the low-frequency or ultra-high-frequency signals can be easily duplicated or coped using a specific hacking device tool especially in this modern era [3]. This situation leads to the risk of EV being stolen.

Therefore, it is necessary to develop a security system to enhance the security of EV. One of the ways is to integrate the EV with biometric which is using facial recognition.

Biometrics are becoming increasingly integral to both personal security setups, providing a strengthen layer of protection. Biometrics use unique body features, such as fingerprints, irises, and facial structures, to authorize access. Thus, one of the biometrics was facial recognition technology. In 1967, Woodrow W. Biedsoe, a pioneer in artificial intelligence, developed a system that can classify photos of face using a graphical computer input device known as RAND tablet. The exponential growth of technology makes facial recognition integral with complex algorithm artificial intelligence, neural network, and machine learning to process, identity, and classify images with a high degree of accuracy.

The problem statement for developing facial recognition using Raspberry Pi module on electrical vehicle (EV) is because there is an increasing number of consumers buying EV as the prices are affordable. However, the EV nowadays uses passive entry passive start (PEPS) system to allow driver access into the vehicle. By using this PEPS system, drivers need to carry the key to unlock their EV. The disadvantage of this system is that driver might lose their key due to the careless behavior causing them need to pay expensive price to replace the key. Furthermore, some EV store their unique code in remote control and driver need to carry it and present in the range of the EV in order to access it, but sometimes the battery of the remote control drain out due to long time in use or the remote control suddenly malfunction. If the key is stolen, the EV can be accessed by who is holding the key.

Given the vulnerabilities of current Passive Entry Passive Start (PEPS) systems and the rising demand for secure keyless access in electric vehicles, it is crucial to explore biometric alternatives that offer both accuracy and reliability. This study seeks to answer the following research question: Can a facial recognition system implemented on a Raspberry Pi using PCA and SVM provide secure and efficient keyless access to electric vehicles while maintaining high accuracy and real-time performance? By addressing this question, the study aims to bridge the gap between low-cost embedded systems and advanced biometric security solutions for EVs.

The solution that is proposed in this project is to implement facial recognition in EV using Raspberry Pi. The Raspberry Pi module is a microcontroller that can configure based on desire function using programming. The module will integrate with

other components such as camera, lock of EV, and engine of EV. The system will provide an interface for driver to use facial recognition to access their EV.

The system of facial recognition in EV will solve the problems of the present EV limited access option and give flexibility. Drivers will be able to access their EV using their facial feature without carrying any key on them. The security system using facial recognition on EV will improve driver experience and simplify the process of unlock EV. The objective for the development of facial recognition in electrical vehicles using Raspberry Pi is to achieve more than 95% accuracy of facial recognition and achieve execution time not more than 3 seconds. To analyze the accuracy and efficiency of the facial recognition system using Receiver Operating curve, and to develop a facial recognition system to access EV with Raspberry Pi. The first step of this project is to create a block diagram to illustrate the facial recognition system in EV. After that, selecting the proper version of microcontroller, sensor, actuator, and other components. The microcontroller will need to program to recognize a person's facial feature and record it into its database then allow access to an authorized person. The microcontroller also needs to control other components such as lock and motor. Decentralized coordination concepts, such as those used in multiarea temperature control systems, can enhance the modular management of EV subsystems [4].

High quality camera module is required in the procedure of facial recognition because it is used to take input (image) from driver. The facial recognition system in EV needs to be programmed using specific algorithm. Thus, a user interface will be necessary for programming and allow users to interact with the system to set up their biometric. Meanwhile, the security system might need to be improved soon. Thus, this requires an LCD panel and a keypad or touch screen panel. In a word, developing a microcontroller-based security system that uses facial recognition in EV required various knowledge, such as microcontroller programming, technical skills, and logic thinking. Iterative design approaches and formal validation techniques, such as model checking, can further enhance the reliability of embedded authentication systems in critical applications [5]. Implementing face detection and recognition technology for unlocking electrical vehicles (EV) has several societal implications. In a word, this technology not only brings convenience it also enhances the security for users. It makes the process of accessing vehicle more simple and easy, reduces the risk of theft, and potentially minimize the chance of losing physical keys. However, societal concerns arise regarding privacy and surveillance. Implementing facial recognition technology may lead to an increase in potential infringing on individual privacy rights. This is because users were concerned about who has access to the facial data and how it is stored.

In terms of health perspective, facial recognition technology may affect user's psychology due to the reason of continuing monitoring by the technology system. Indirectly, this can lead to stress and anxiety among users. The facial recognition in EV must be very sensitive and accurate in detecting user's face to avoid potential safety hazards. It is equally important to address functional safety in the communication layers, especially when facial data is transmitted over embedded networks [6].

System malfunction or misrecognition could lead to unauthorized access or system lock users out of their vehicles. Thus, reliability and accuracy of the facial recognition technology must be considered first before implementing the EV. When it comes into legal issues, engineers must ensure that their systems obey with local, national, and international laws regarding data protection and privacy. Issues such as data permission, storage, and sharing must be addressed in compliance with legal standards. Furthermore, there could be legal liabilities in case of system failures or breaches that lead to unauthorized access or harm. In some cultures, there is a high acceptance and trust in technology. Meanwhile, there is controversy and concern about privacy and surveillance. Engineers must consider these culture differences when designing and implementing facial recognition systems. One of the ways to address these issues is to carry out a survey with communities to understand their concern.

The main contributions of this research are as follows:

- The study implements a face detection and recognition system to enhance biometric security in electric vehicles.
- The proposed system integrates Principal Component Analysis (PCA) with Support Vector Machine (SVM) to improve facial recognition accuracy.
- A real-time face recognition system is deployed on a Raspberry Pi platform, ensuring a cost-effective and efficient security solution.
- The performance of the proposed system is evaluated using accuracy metrics and the Receiver Operating Characteristic (ROC) curve, achieving 95% recognition accuracy.
- The system offers a keyless vehicle access mechanism, improving user convenience while mitigating the risks of key theft and duplication.

The paper proceeds as follows: Section II reviews existing methods relevant to the current study. The proposed approach is presented in Section III. Section IV presents the experimental results, while Section V discusses the findings in detail. Section VI outlines the conclusions drawn from the study, and Section VII highlights the limitations and proposes potential directions for future work.

## II. Literature Review

A literature review is a critical overview and assessment of the body of work such as books, academic articles, dissertations, or conference papers that have already been published regarding a specific subject or research question. It involves reviewing, assessing, combining relevant materials to present a summary of the state of knowledge in a specific field or topic area. In this chapter, reviews on explanation on algorithm used, past studied, and project regarding the implementation of Facial Detection and Facial Recognition and all its component that will be explained.

In this study [7], the author has shown that there are three important stages in the structure of Face Recognition to produce a robust system. The first stage was face detection and obtain input either in image or video to locate the position of human

face. Secondly, the feature extraction was the stage to extract the unique feature of human face such as eyes, nose, mouth, and mustache for any human faces located in the first stage. Lastly, the stage of face recognition uses the features extracted from the human face to compare it with all templates faces in database to decide the human identity. Fig. 1 shows the structure of face recognition by [8].

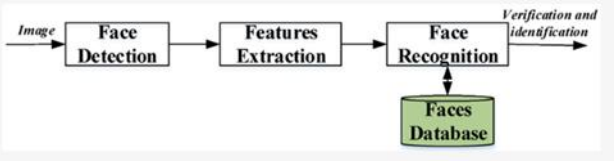


Fig. 1. Structure of face recognition.

### A. Face Detection

Face detection is an algorithm used to detect the presence of a human face, serving as a crucial preprocessing step for face recognition [9]. The system will create a box bounding if the human face is in detection, the box will be in green color [10]. One of the most famous algorithms used in face detection was Viola Jones's algorithm, known as Haar-Cascade algorithm.

### B. Haar-Cascade algorithm (Viola Jones's algorithm)

The algorithm was proposed by Viola and Jones in 2001. The algorithm is used in various applications that apply face detection because it can recognize faces in a real time video [11]. Human's facial features can be differentiated from a set of data image by using Haar feature. Haar features were proposed by Alfred Haar in 1909. The detector of cascade detects the face in the captured mage or real-time and face region is extracted. The face image was normalizing to remove the noise or unwanted information due to other factors while capturing the image [12].

### C. Face Recognition

Face recognition is a process of identifying or giving access to an individual using their face without physical contact with any hardware. Sun and Chen [13], originally proposed a method for face recognition. Today, this approach is widely used in modern systems. Face recognition is mostly used to identify people in photos, videos, or in real-time. In nowadays, the accuracy of face recognition system can be improved using machine learning, the system is trained using images of authorized users, and the accuracy of recognition can be enhanced [14].

### D. Principal Component Analysis (PCA)

PCA was proposed in 1901 by Karl Pearson, who introduced the idea and implemented it to non-random variables [15]. Harold Hoteling extends the concept of Karl Pearson to random variable in 1930. Nowadays the technique is applied in various fields, including mechanics, economics, medicine, and neuroscience. In computer science, PCA is used as a tool for data dimensionality lowering. In the era of Big Data, the data we process was large and complicated. Thus, PCA can reduce computational complexity and save computer storage. Next, face recognition benchmarks that used PCA have been achieved using machine learning and are applied in research and commercial application [16].

### E. Support Vector Machine (SVM)

SVM is an algorithm that was developed in 1990 by Vladimir N. Vapnik and his team [17]. SVM was mostly used in classification problems. The algorithm was recommended in solving binary classification. SVM can differentiate between two classes by calculating the optimal hyperplane that maximizes the margin between the closet data points of opposite classes. Furthermore, SVM can be categorized as a supervised deep learning algorithm, which is frequently used in the process of classification models and regression problems. Recent studies have also demonstrated the potential of SVM for secure, real-time decision-making in intelligent systems, including blockchain-based environments in the Internet of Medical Things (IoMT) [18].

### F. Related Works

In this research paper of using Facial detection and Facial recognition in EV using Raspberry Pi, the important key in this system was the algorithm that implement. Thus, researchers have reviewed several papers that propose different algorithms for face detection and face recognition. One of the papers by Khairul Anuar Ishak [19], presents a system using face detection and face recognition to unlock the door and ignite the engine of vehicle, the algorithm they used for face detection was the combination of Fast Neural Network and Convolution Neural Network while the algorithm used for face recognition was the combination of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). The study of the paper aim to improve the accuracy of face detection and face recognition when drivers want to access the vehicle. The combination of the algorithm used in the system shows the highest recognition rate and lowest misclassification rate. The system proposed in this research paper shows the total processing time for driver access to a vehicle with 5.1 seconds and the average recognition rate of 91.43%.

Another research paper by SL LIN and JY WU [20], the facial recognition system used FlagBlock building block program software of Flag Maker. The program creates a website for browser connections to use facial recognition, so that the user can get output and input of the information of D1mini. The author used mobile phone or computer browser as D1mini output interface. Principal Component Analysis (PCA) as the algorithm for analysis through the experiment, two-dimensional PCA was chosen by the author and found out that recognition correctness showed good results compared to the rate of accuracy of original image. 300 face photos were used for training for PCA analysis, and the test was carried out 100 times. The results for recognition rate were 92%. The success rate was dependent on the situations, such as lighting conditions, distance, and the angle of the face.

Next, authors Chaitanya Kolluru, Akhil GV and their colleague propose a research paper "Development of Face Recognition-Based Smart Door Lock System with Remote Servo Control Authentication" [21]. The proposed project used Haar-Cascade for the face detection, OpenCV library was used for image processing to detect the multiple faces. Then the author integrates the system with AdaBoost machine learning, the machine learning chooses the most relevant Haar-like features from a large number of features. The author used Dlib's algorithm for facial recognition, the algorithm uses deep metric learning by using a neural network called Reset. This method

learns a mapping from face image to a high dimensional feature space because some faces will have same feature from different people. The system used Raspberry Pi board with a camera module, Motion sensor responsible for motion detection during low-light condition while the servo motor control for door lock. The proposed system achieved 92.72 % of accuracy when the system was trained with 1000 image and achieve 80.24% accuracy rate in low light.

In [22], the research paper proposed a system to ignite vehicle using facial recognition. The system used Convolution Neural Network (CNN) models as the machine learning for to recognize the authorize person. During the training session, author choose four different people as input image for CNN models, each person has 500 of image. The backbone of the CNN model used for facial recognition have four layers and it will produce stage by stage using the same layer. The first layer was the input layer, this layer carried out images from the pre-processing stage. The second layer was the three stages of convolution layers, each consisting of a convolution operation and a rectified linear unit (Relu). The third layer implemented fully connected layer. The final layer was a dropout layer, utilizing four classes of face images in CNN model for facial recognition. The proposed model has achieved 98.3% of accuracy for face recognition.

The purpose of the project is to enhance the security of the vehicle by using face recognition to ignite the car's engine. The proposed system uses cascade detectors that recognizes the obtaining image and extract the feature of the face region. OpenCV was used for face recognition operation, the operation was done using variety of algorithm, including feature-based and model-based algorithm. The research paper stated that LDA (Linear Discriminant Analysis (LDA)) was better than PCA (Principal Component Analysis) when big training sets was applied in recognition. The accuracy of the proposed system achieved more than 80% when come into confirming the identity of user with the saved image of user in the system [23].

In this research paper [24], author has made an evaluation of the performance of facial recognition model based on multiple algorithms. Algorithms which are used were Support Vector machine (SVM), Local Binary Patterns Histogram (LBPH), Eigen faces (EF), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA). The datasets used for the training was from ImageNet and Scikit Learn tool and was used to determine the accuracy, precision, recall, F1-Score and execution time for each method. The execution time for each algorithm can be rated as PCA<SVM<LBPH<LDA<EF. However, from the perspective of precision and accuracy of the algorithms, SVM performs better than another algorithm which are 98% for both perspective.

On the other research paper [25] by Asif Rahim and his team, they enhance the performance of face detection and facial recognition in smart home system by using logistic regression (LR), Hist gradient-boosting classifier (GBCs), and convolutional neural network. The reason for authors to enhance the system was because, the factors of illumination condition, facial expression, pose, occlusions and aging pose affected the accuracy of face recognition. The proposed models also compare with LR-XGB (XGBoost)-CNN, LR-CBC (CatBoost Classifier)-CNN, LR-GBC (GradientBoost)-CNN, LR-ABC(AdaBoost Classifier)-CNN, and LR-LGBM(LightGBM classifier)-CNN, and were evaluated based on their functionality using a dataset containing sensor readings and face images. Among these, the LR-HGBC-CNN model has shown a good results compared with other model because it achieved high scores across multiple metrics such as accuracy, precision, recall, F1 score, and AUC-ROC in both anomaly detection and facial recognition tasks. Specifically, the LR-HGBC-CNN model reached an accuracy of 94% for anomaly detection and 88% for facial recognition, indicating its robust capability in distinguishing normal and abnormal events as well as recognizing authorized faces in smart home environments.

In this research paper [26], the author develops a hardware that can capture image of kidnapper and perform face recognition on the suspect to help victims' family to rescue their children in shortest period. The face detection method used by the author was Viola-Jones algorithm. The author used Convolution Neural Network (CNN) to perform the facial recognition system [27]. The dataset that was used by author was AT&T database, Celab Faces Attributes dataset, and face dataset that are collected by author and the outcomes are 87.50%, 92.19% and 95.93% respectively. Overall face recognition accuracy was 98.48%.

In [28], author had demonstrated the face recognition using algorithm Local Binary Pattern Histogram (LBPH). The objective of the study was to produce a biometric security system for better function. The biometric system was integrated with augmented reality (AR) and the face recognition rate was achieved at 90% in bright lighting conditions.

In this research paper [29], the study focuses on developing a system that can process fast face recognition so that it can monitor student attendance in smart classroom. The proposed method based on Convolution Neural Network (CNN) and able to detect 30 faces out of 35 detected faces [30]. They use Edge Computing for processing the data at the edges of the nodes to reduce the data latency and enhance the real time response. Their proposed system had made accuracy of 85.5% in face recognition and 94.6 % in face detection.

From [31], author had developed a face recognition for absence information system. The study stated that the face recognition system can apply Principal Component Analysis (PCA) and Support Vector Machine (SVM). The author used customize dataset which is 100 facial data for test data and training data. The system test results showed that the use of PCA and SVM as a classifier can achieve a high level of correctness. The training included the facial image, 91% of the identification was correct.

While numerous studies have explored face recognition using PCA, LDA, CNN, and other algorithms, most have focused on controlled environments or high-performance computing platforms. Few have investigated the feasibility of integrating PCA and SVM for real-time face recognition on embedded, low-cost platforms such as Raspberry Pi [32], [33]. Additionally, although prior works achieved recognition accuracies ranging between 85% to 92%, there is a lack of comprehensive evaluations that simultaneously address execution time and recognition accuracy in EV security

contexts. This study aims to fill this gap by implementing and evaluating a PCA + SVM-based face recognition model on Raspberry Pi, emphasizing both security performance and real-time responsiveness, specifically for EV access systems.

## III. PROPOSED METHOD

To develop a system that can recognize human facial using Raspberry Pi module, a hardware device such as Raspberry Pi 4 module, is used to capture the face image of the authorize person, which serve as input image to the facial recognition. A custom face dataset is necessary for training and testing the correctness of the proposal system. The components used for the hardware are the Raspberry pi 4 module, LED light, PIR Motion Sensor, Camera Pi module, breadboard, Lan cable, and power adapter [34]. To make the Raspberry Pi as a standalone hardware for face recognition system, MATLAB software is used for deep learning in facial detection and facial recognition [35]. After the accuracy of the system is reached as our objective which is to achieve more than 95%, the program will be deployed to the Raspberry Pi board through LAN cable. Fig. 2 shows the block diagram of the system. Several studies have explored similar microcontroller-based integrations using ESP32, ESP8266, and Arduino platforms for IoT and control applications [36], [37] and [38], validating their effectiveness in real-time monitoring and system automation.

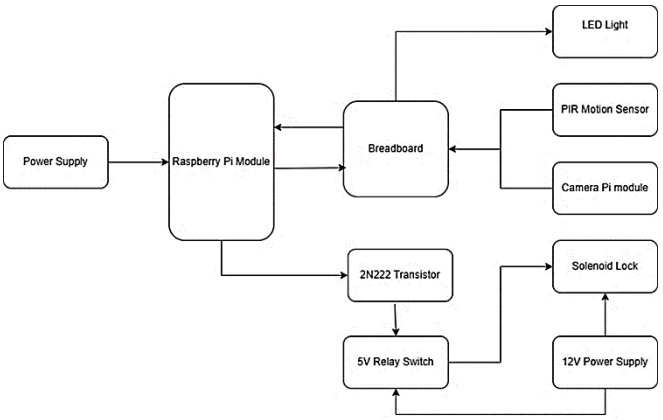


Fig. 2. Raspberry Pi face recognition block diagram.

### A. Programming Flowchart

Based on Fig. 3, the flowchart shows a person's facial feature is set and recorded as a template in the database before the face recognition process start. The system (Raspberry Pi) was powered by a 5V direct current and will always be in the standby mode. The motion sensor will detect the presence of human and turn on the system, the system starts detecting and isolate a human face in a rectangle that indicate the region of interest. After that the camera will capture the image through the camera module (Raspberry Pi Camera module) [39]. If fail to capture the human's face the system will deny the access. After the capturing is successful, the captured human's face will be compared to the face template that is set on the database. After that, the system would make decision, if the face matched with the face template in the database, then the access will be granted. However, for the unmatched face, the system will show a message "Access Denied".

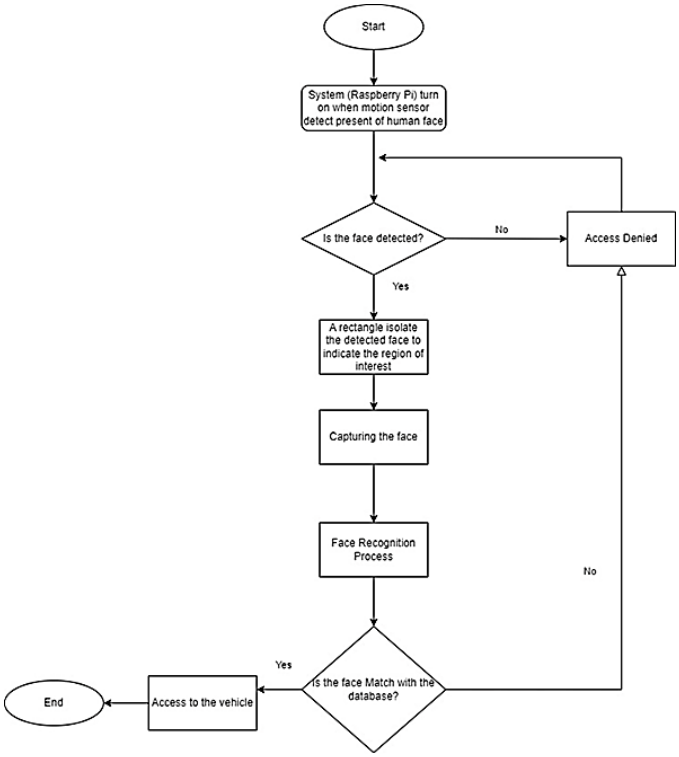


Fig. 3. Programming flowchart.

### B. Dataset

A dataset is important for face recognition system. When it comes to stage for testing the accuracy of the algorithm, a quality dataset ensures that the algorithm is able to differentiate one face from another. This includes understanding in facial features, angle, and lighting conditions. When an algorithm was trained and achieve high accuracy of face recognition, meaning it can accurately recognize faces it has never seen before by using the general features of human faces. To achieve high accuracy of face recognition. Researchers use AT&T dataset which consists of 400 human faces and a custom set of databases which consists of 200 human faces to test the system efficiency.

### C. Algorithm

The method used to design the proposed work was the combination of Principal Component Analysis and Support Vector Machine (SVM) to develop a facial recognition system. Viola- Jones's algorithm is vital in the face recognition as it is the first step in face recognition. This algorithm developed for general object detection, and it can be trained to an algorithm that can detect human face only. According to [40], there are four main steps in Viola- Jones's algorithm which were Choosing Haar-like features, creating an integral image, Running Adaboost training, and Creating classifier cascade. An input data (image) is segmented into tiny of size NxN and convert into rectangle area and features are calculating individually every single rectangle. Human face have shared some similarities, for an instance, the nose region tends to be brighter than the mouth region and the eye region are typically darker compared to the forehead. Fig. 4 shown the basic Haar-like Rectangle features.

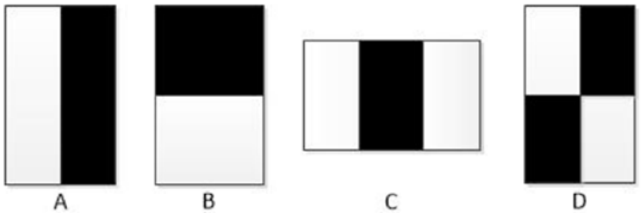


Fig. 4. Basic Haar-like rectangle features.

Haar-like features are efficiently calculated apply an intermediate representation known as the integral image, which accelerates computation. In Eq. (1), it computes the integral images. Total of the pixels above and left of (x, y) was included in the integral image which locate at x, y.

$$(x,y) = \sum_{s=1}^{x}\sum_{t=1}^{y} I(s,t); 1 \le x \le M, 1 \le y \le M \quad (1)$$

The integral image was represented as 'A' as shown in Fig. 5. The original image is represented by 'I'. The rectangular region represents as 'M'. The integral image at location 1 in Fig. 5 equals to the total of the region 'A'; while in location 2, A+B is the sum of pixels in region; the total pixel in region C+A was located at location 3; lastly, the summation of the pixel in the region A+B+C+D is locating at location 4.

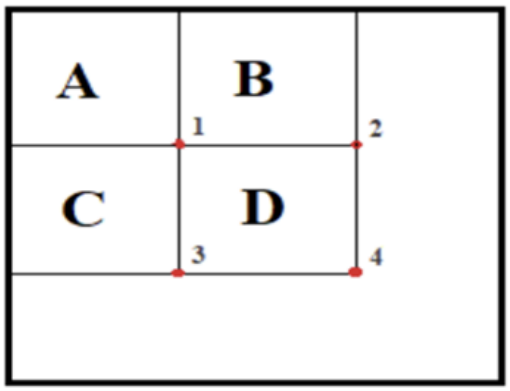


Fig. 5. Integral image formation.

Adaboost algorithm used to reduce the redundancy because the Haar features calculate in every single window is very huge (estimate 180000). The majority of the features are unnecessary. Cascading classifiers [41] will reduce the number of calculated images and selecting the perfect features in every window. PCA is utilized to extract features from the segmented images, serving as the basis for the recognition process by preserving essential information while reducing data dimensionality. To enhance the recognition technology's performance, a beta prior is incorporated, and a full-probability Bayesian model is developed, offering an improvement over the conventional PCA approach. Face recognition technology, as a biometric identification method, leverages computer vision to analyze facial images and identify key feature points such as the eyes, nose, and mouth. Fig. 6 shows the steps for cascaded classification by stages [42].

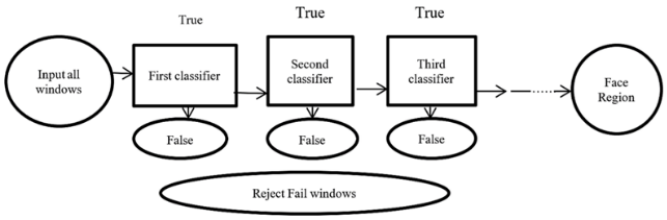


Fig. 6. Steps for cascaded classification by stages.

There are three formulas, Eq. (1), Eq. (2), Eq. (3) used in Principal Component Analysis which were mean, standard deviation and variance.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (2)$$

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - mean)}{n-1}} \quad (3)$$

While the data is often multi-dimensional in computer science. The relationship between two random variables can be described through covariance, Eq. (4):

$$cov(X,Y) = \frac{\sum_{i=1}^{n} X_i - mean\ of\ X(Y_i - mean\ of\ Y)}{n-1} \quad (4)$$

Multiple covariance needs to be calculated as Eq. (5) as the dimension increases. For example, the quantity of covariances required for handling n-dimensionally data:

$$\frac{n!}{(n-2)!*2} \quad (5)$$

Eq. (6) shows the matrix methos give a solution for this solution:

$$C_{n*n} = \left(c_{i.j}, c_{i.j} = cov(Dim_i, Dim_i)\right) \quad (6)$$

Covariance matrix, Eq. (7) was a dataset in three dimensions {x, y, z}:

$$C = \begin{pmatrix} cov(x,x) & cov(x,y) & cov(x,z) \\ cov(y,x) & cov(y,y) & cov(y,z) \\ cov(z,x) & cov(z,y) & cov(z,z) \end{pmatrix} \quad (7)$$

It can be observed that the covariance matrix is a symmetric matrix because the diagonal shows the variance of each dimension. After obtaining the covariance matrix, eigenvalues and eigenvector can be calculated using Eq. (8):

$$A\alpha = \lambda\alpha \quad (8)$$

'A' stands for the original matrix while λ stands for an eigenvalue of A, and α represents the eigenvector according to eigenvalue λ. The study in [43] shows two stages in face recognition using Principal Component Analysis which are training stage and testing stage.

In [44], [45] and [46], Support Vector Machine (SVM) method in machine learning, valued for its capability to handle high-dimensional data and its robustness against noise. Praised for its ability to manage high-dimensional data and its resilience to noise. In the context of a set of training data (Xi, yi), where, Xi represents the feature vectors and yi denotes the class labels, the purpose of SVM is to determine the optimal hyperplane. Below is shown the Eq. (9):

$$W^T x + b = 0 \quad (9)$$

W represents the impact vector, x denotes the input feature vector, b is the bias term. This purpose is to maximize the margin between the hyperplane and the support vector, which are the closet points to the hyperplane form both classes. The optimization problem can be formulated as Eq. (10):

$$\min(w, b)\frac{1}{2}||w||^2 \quad (10)$$

Subject to Eq. (11):

$$y_i(w^T x_i + b) \geq 1 \quad (11)$$

The accuracy of the proposed work can be measured by using the formula, Eq. (12) by [47], [48] which were using True positive, True Negative, False Positive, and False Negative:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} * 100\% \quad (12)$$

ROC curve represents the curve of sensitivity (True positive rate) against 1-specificity (False Positive Rate) while varying the threshold. Different cut-off points are responsible for generating this graph. The AUC (area under the curve) quantifies the effectiveness across various test thresholds on the ROC curve. Fig. 7 shows an example test with an AUC of 1.0 is very accurate as the sensitivity reaches 1.0 while specificity also archives 1.0.

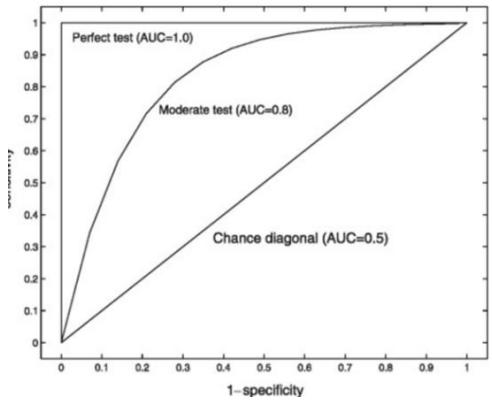


Fig. 7. ROC curve.

### D. Circuit Design

Fig. 8 shows the circuit connection between Raspberry Pi module, Relay Switch, 12V battery, Solenoid lock, Pi Camera Module, and PIR sensors. In this project, researchers use Raspberry Pi GPIO pin to communicate with other components. Below Fig. 9 shows the GPIO pin with label for better understanding.

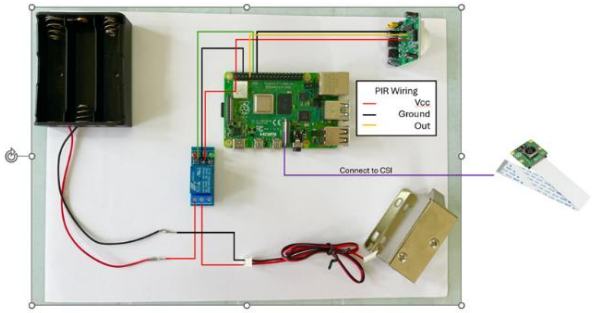


Fig. 8. Circuit design.

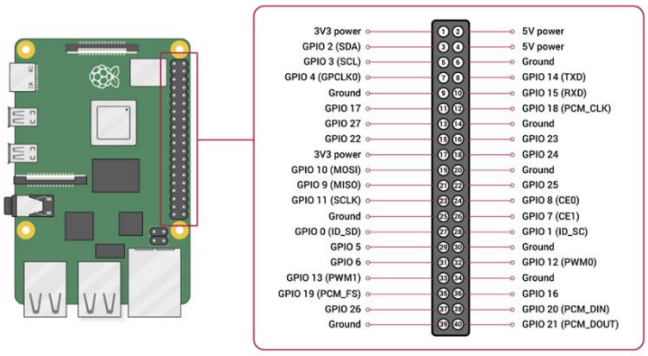


Fig. 9. GPIO pin in Raspberry Pi.

## IV. Result

The proposed work starts with testing the algorithm in MATLAB software by using the application of classification learner. The dataset of 10 people was prepared and divided into classes, each class contain 10 images. After that, the dataset was converted into table firm since the classification learner only accept dataset in table form. The classification learner can analyze the reliability of the input dataset by using the algorithm of PCA and SVM. Fig. 10 shows the results of using classification learner to test the input dataset:

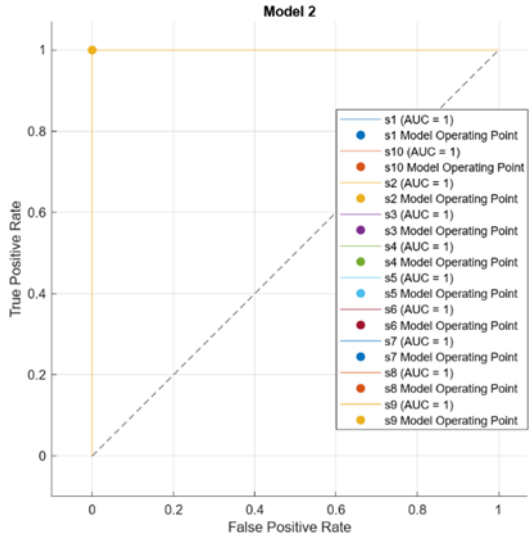


Fig. 10. ROC Curve for 10 people.

From the ROC, each person was named for ‘s’. Thus, there were 10 class, and each class represented a different person. The area under the ROC curve (AUC) represents the probability that the model. From the results, we can conclude that every class where, the area under the curve (AUC) were 1.0, which mean the classifier can perfectly differentiate between positive and negative classes.

### A. Test the Custom Face Database with PCA and SVM

The custom face dataset was needed to pre-process by converting the images into table form before the training session. Before converting the images into table form, the dimensions of images were fixed at 180 (width) x 200 (height). The number of components was a crucial step in determining the accuracy of the model. If fewer components were selected it would reduce

computational complexity but may lose some information. However, more components retain more information but increase complexity. In this part, researchers used 50 components for 250 images to test the performance of the model. The Fig. 11 shows the accuracy of the training results:

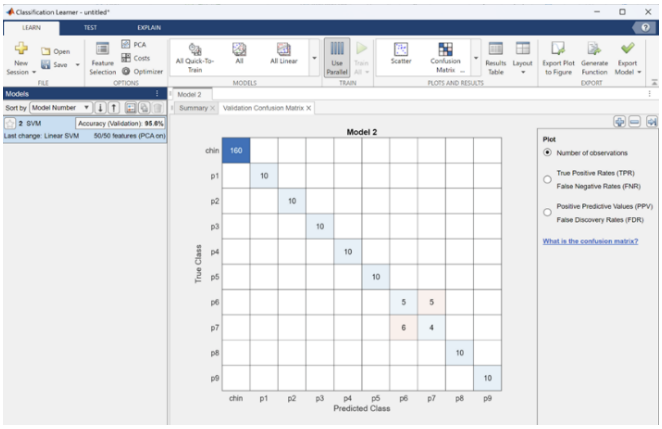


Fig. 11. The Acccuracy using PCA and SVM using 250 images.

To test the accuracy of the proposed face recognition model, the True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP) were recorded in Table I. The table shows the value of each class in model training:

TABLE I. FACE RECOGNITION RESULTS OF CUSTOM DATABASE

| Class | Testing Images | TP | TN | FN | FP | Accuracy |
|---|---|---|---|---|---|---|
| chin | 10 | 10 | 0 | 0 | 0 | 100% |
| P1 | 10 | 10 | 0 | 0 | 0 | 100% |
| P2 | 10 | 10 | 0 | 0 | 0 | 100% |
| P3 | 10 | 10 | 0 | 0 | 0 | 100% |
| P4 | 10 | 10 | 0 | 0 | 0 | 100% |
| P5 | 10 | 10 | 0 | 0 | 0 | 100% |
| P6 | 10 | 5 | 3 | 0 | 2 | 80% |
| P7 | 10 | 4 | 3 | 1 | 2 | 70% |
| P8 | 10 | 10 | 0 | 0 | 0 | 100% |
| P9 | 10 | 10 | 0 | 0 | 0 | 100% |
| | Total | 89 | 6 | 1 | 4 | - |
| Average Accuracy | | | | | | 95% |

The table presents the classification performance of a model across ten different classes, each with 10 testing images, totaling 90 images. The model achieved perfect accuracy (100%) for most classes, including chin, P1, P2, P3, P4, P5, P8, and P9, correctly identifying all instances. However, performance dropped for P6 and P7, with accuracies of 80% and 70%, respectively, due to false positives and false negatives. The overall accuracy of the model is calculated at 95%, indicating strong general performance. The errors in P6 and P7 suggest potential challenges in distinguishing these classes, which may require further investigation, such as improving feature extraction, enhancing the dataset, or optimizing the model parameters. Expanding the testing dataset could provide additional insights into performance trends and areas for improvement.

The execution time was measured using the average method, where the test was conducted 20 times to ensure consistency and reliability of the results. Table II shows the recorded time and average time for the code execution:

TABLE II. AVERAGE TIME FOR CODE EXECUTION

| Test | Time (s) |
|---|---|
| 1 | 2.32 |
| 2 | 2.45 |
| 3 | 2.37 |
| 4 | 2.32 |
| 5 | 2.54 |
| 6 | 2.29 |
| 7 | 2.29 |
| 8 | 2.29 |
| 9 | 2.28 |
| 10 | 2.30 |
| 11 | 2.31 |
| 12 | 2.27 |
| 13 | 2.28 |
| 14 | 2.33 |
| 15 | 2.31 |
| 16 | 2.38 |
| 17 | 2.39 |
| 18 | 2.30 |
| 19 | 2.28 |
| 20 | 2.28 |
| Average | 2.32 |

### *B. Test the Face Recognition with Raspberry Pi*

After the testing had done in MTALAB, the proposed work has been moved into Raspberry Pi to test. When there is presence of face, region of interest (ROI) will isolate the face region and capture the image [49]. The purpose of doing this is to carry out a real time facial recognition in Raspberry Pi to let user unlock the vehicle door. Fig. 12 shown the results of using Raspberry Pi execute the command.

Fig. 12 also shows the results when authorized face was detected. While Fig. 13 shows the results when unauthorized face was detected and ‘unknown’ was shown in the window screen.

The time for the system detects the face was 2.32 seconds by using the average method to calculate the time. While the accuracy when compared with previous work had shown that the accuracy has been improve using PCA and SVM. Table III shows the comparison of the accuracy.

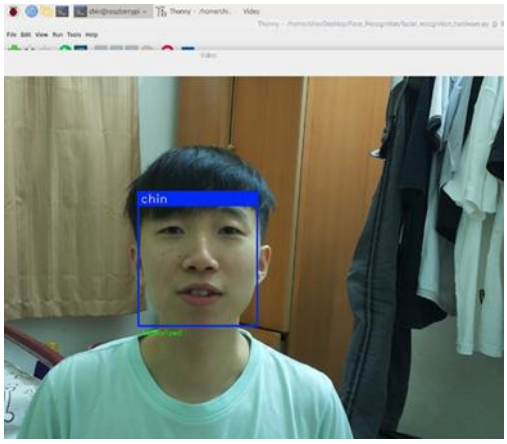


Fig. 12. Face recognize using Raspberry Pi.

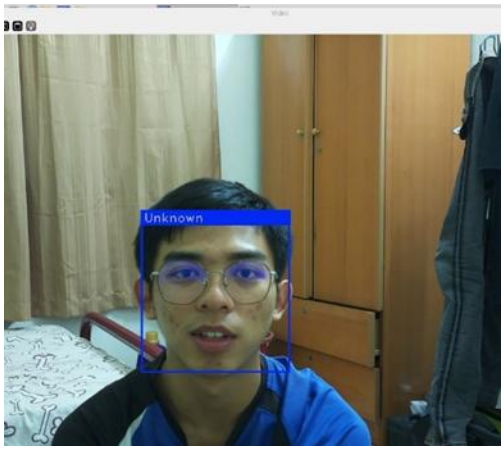


Fig. 13. Unauthorized faces detected.

TABLE III. COMPARISON OF ACCURACY IN FACE RECOGNITION ALGORITHM

| Ref. | Algorithms used in Face Recognition | Database | Accuracy (%) |
|---|---|---|---|
| [15] | PCA + LDA | Customize | 88.75 |
| [16] | PCA | Customize | 92.00 |
| [17] | Haar-Cascade + Dlib's face recognition | Customize | 92.72 |
| [20] | PCA +LDA | Customize | 80.00 |
| [23] | CNN | AT&T | 87.50 |
| [24] | LBPH | Customize | 90.00 |
| [25] | CNN | WILDS | 85.5 |
| [26] | PCA + SVM | Customize | 91.00 |
| Proposed algorithm | | Customize | 95.00 |

The accuracy of facial recognition using a different algorithm and database is recorded in Table III. Compared to existing studies, the proposed PCA + SVM-based facial recognition model offers several distinct advantages. First, it achieved the highest recorded accuracy of 95% among all reviewed works, surpassing traditional PCA + LDA, LBPH, CNN, and Dlib-based methods. Second, the model maintained low execution time (2.32 seconds), demonstrating real-time capability on a resource-constrained Raspberry Pi platform—something not addressed in most prior works. Additionally, unlike many previous implementations that rely on high-performance systems or require complex hardware integration, this model offers a cost-effective and scalable solution suitable for embedded vehicle environments. These advantages validate the practicality and effectiveness of the proposed system for EV security applications.

## V. DISCUSSION

From the outcome, researchers have achieved all the objectives which is to achieve more than 95% accuracy of facial recognition, use ROC curve to analyze the accuracy of the face recognition, and develop the Face recognition using Raspberry Pi. When the system captures the human face, the system will undergo Principal Component Analysis to extract the significant features of the face and undergoes Support Vector Machine (SVM) to improve predictive accuracy. Before the software was implemented into Raspberry pi board, the software was evaluated with Receiver Operating Curve (ROC), the curve uses a graphical to measure the performance of a classification model. It plots the trade-off between the True Positive Rate (TRP) and the False Positive Rate (FRP) at various threshold settings. The environment must have enough lighting to make sure the camera can capture a clear facial image. The average time for the system to recognize an authorized face was about 95% and the time execution was 2.32 seconds.

The theoretical foundation of this work—specifically the use of Principal Component Analysis (PCA) for feature extraction and Support Vector Machine (SVM) for classification—is motivated by the need to implement a high-accuracy, real-time face recognition system on a resource-constrained embedded platform. By validating these algorithms through MATLAB and then deploying them on a Raspberry Pi, the study demonstrates the practical viability of transferring machine learning theory into real-world automotive security systems. This approach not only strengthens biometric security in electric vehicles but also showcases the potential for broader applications in other IoT-based systems requiring fast and reliable biometric authentication.

The validation of the proposed facial recognition system was performed using both a standard (AT&T) and custom dataset. We evaluated the model using precision metrics, including ROC curves and AUC scores. The AUC consistently reached 1.0 across 10 classes in the ROC test, indicating perfect classification performance. Furthermore, Table III provides a comparative analysis of our model against other recent approaches, highlighting superior accuracy and real-time responsiveness.

The accuracy of facial recognition using a different algorithm and database is recorded in Table III. The results show the accuracy of the proposed algorithm has the highest compared to other previous studies. The proposed algorithm proved that the accuracy of the PCA + SVM was improved compared to previous studies. This also shows that the objective number two was achieved by using SVM to analysis the system.

## VI. CONCLUSION

This thesis presents the development and implementation of face detection and face recognition systems using Principal

Component Analysis and Support Vector Machine (SVM). The proposed system was divided into two parts, the first part was to analyze the reliability of the system using MATLAB software. After the system achieved 95% of accuracy above, the system was implemented in Raspberry pi board to test out with the component. The combination of both parts ensured work as a standalone device to let driver using shortest time to access their EV and increase the security of the vehicle.

This research also aimed to identify the best methods for the proposed Principal Component Analysis (PCA) and Support Vector Machine (SVM). To increase the accuracy of the system, the training photo was important, which is the size, number of training images and the resolution choose. At first the system was trained at 100 images and the accuracy was not achieved, then the training image was increased to 200 images, the accuracy improveed to 95% above. This shows that the more training images the higher the accuracy of the system.

## VII. Limitation and Future Works

The limitation of the proposed methodology is that, it is time consuming in creating the face dataset. More images indicate that more individuals are required to create a customized dataset. Next, the quality of the images, the training images must have the same properties in terms of size, resolution and lighting of environment. There is also a limitation for the system which is the system can recognize a photo of an individual which means an individual can use a photo to access the system. The proposed system was aimed at improving the security of nowadays EV. The system can be installed on the door frame of the vehicle. The system ensures that only authorized person can have access to the vehicle. Besides, the proposed system can also be implemented in the home security system.

## Conflicts Of Interest

The authors declare no conflict of interest.

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## Authors' Contributions

The authors' contributions are as follows: "Conceptualization, Jamil Abedalrahim Jamil Alsayaydeh and Chin Wei Yi; methodology, Fatimah Abdulridha Rashid; software, Jamil Abedalrahim Jamil Alsayaydeh; validation, Fatimah Abdulridha Rashid; formal analysis, Chin Wei Yi; investigation, Jamil Abedalrahim Jamil Alsayaydeh; resources, Fatimah Abdulridha Rashid; writing—original draft preparation, Jamil Abedalrahim Jamil Alsayaydeh and Safarudin Gazali Herawan; writing—review and editing, Chin Wei Yi and Rex Bacarra; funding acquisition, Rex Bacarra and Safarudin Gazali Herawan.

## Data Availability Statement

All the datasets used in this study are available from the Zenodo database (accession number: https://zenodo.org/records/15034216).

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# Modelling the Moderating Role of Government Policy in Cryptocurrency Investment Acceptance

Maslinda Mohd Nadzir[1], Rabea Abdulrahman Raweh[2], Hapini Awang[3], Huda Ibrahim[4]
School of Computing, Universiti Utara Malaysia, Malaysia[1, 2, 4]
Institute for Advanced and Smart Digital Opportunities-School of Computing, Universiti Utara Malaysia, Malaysia[3]

***Abstract*—Without the requirement for third-party approval, cryptocurrency enables anonymous, secure, quick, and inexpensive financial transactions. Although cryptocurrency is gaining global popularity, its applications are still limited. This research aims to investigate the factors influencing the acceptance of cryptocurrency as an investment tool, focusing on the moderating role of government policy. Using the Unified Theory of Acceptance and Use of Technology (UTAUT) extended with awareness, security, and trust, a survey was conducted with 220 respondents. Structural Equation Modelling (SEM) was employed to analyse the data. The findings revealed that the usage of cryptocurrencies is significantly affected by performance expectancy, facilitating conditions, social influence, awareness, and security in investment. However, trust does not affect the acceptance of cryptocurrency as an investment. The outcomes generate vital insights and strategies for cryptocurrency users, offering a crucial examination for stakeholders and professionals keen on understanding the underlying dynamics of cryptocurrency acceptance in investment.**

***Keywords*—Cryptocurrency; acceptance; investment; UTAUT; government policy***

## I. INTRODUCTION

Globalisation has recently improved many facets of people's lives, communication techniques, and company processes, bringing about major changes [1]. Although its effects haven't been uniform, humanity's global interconnectedness has opened up new opportunities [2]. Concerns over the impacts of globalisation have been highlighted by a few corporate scandals that have received criticism [3], [4]. Cryptocurrency, also referred to as payment tokens, crypto tokens, electronic currency, cyber currency, virtual commodities, and virtual assets, these digital currencies work similarly to physical currency but conducts transactions via blockchain technology [5]-[7]. Cryptocurrency allows for peer-to-peer transactions directly, circumventing banks and government regulation, in contrast to traditional currency [8], [9]. This gives cryptocurrency users alternatives to fiat money or debit/credit cards [10]. Bitcoin is considered to be the original cryptocurrency, having been created by Satoshi Nakamoto in 2008.

Cryptocurrency is becoming used for more than only small-scale transactions like Bitcoin trading and hiring programmers [11]. Pizzas were purchased for 10,000 Bitcoins, or $25 at the time, in the first known business transaction, which is an interesting turning point in the history of Bitcoin. This transaction signalled the start of the currency's exponential rise in value. Within the category of crypto-assets, digital currency was recognized as an investment and has developed into a speculative tool for short-term trade. Bitcoin, in particular, has become a commonly recognised medium of exchange and transaction currency despite fluctuating significantly [12]. By 2021, the price of a single Bitcoin was about USD 67,000, indicating a significant increase from its launch twelve years earlier. Notably, El Salvador was the first country to officially recognize Bitcoin as a legal tender, which helped it become well-known worldwide [13]. Although its prices are still unregulated, Bitcoin trading works differently because it occurs on licensed exchanges. Since its debut, several new cryptocurrency investment products and exchange-traded funds have been introduced, further solidifying Bitcoin's reputation as a credible trading and investing option. It was thought that cryptocurrency could be a game-changing technology that could solve enduring problems in business and finance [14]. Similarly, as of May 2020, about 5,400 distinct cryptocurrencies were available. Bitcoin has the highest market capitalization at US $160 billion [15]. This translated into around 300 million cryptocurrency users worldwide, with 5.8 to 11.5 million active wallets. These developments highlight the potential for cryptocurrencies to transform the established financial system and establish themselves as a significant medium of exchange [16]. However, despite these achievements, the scope and geographic reach of Bitcoin adoption and spread are still somewhat constrained. [17]. Consequently, cryptocurrency has yet to fully realise its potential, as widespread acceptance is still lacking [18]. Researchers critically studied cryptocurrencies, mostly concentrating on their application in Western settings [19], [20], as such academic research on cryptocurrencies is still limited, particularly in developing nations [21]. Researchers like [22], [23] observed that although cryptocurrencies are growing in underdeveloped countries, they are still in their infancy. Furthermore, only a limited number of stakeholders regularly interact with this currency, even though many have a sufficient understanding of it [24]. The conversation around cryptocurrencies did not take off until 2011, and reputable peer-reviewed journals did not publish articles about cryptocurrency until 2013 [25]. As a result, knowledge about cryptocurrencies is still scarce, especially regarding other well-known financial technologies like internet banking or mobile payments. Furthermore, prior studies on blockchain adoption and cryptocurrencies have mostly concentrated on advanced countries such as the USA and the UK [26], [27].

As a result, a limited amount of literature has been done on the acceptability of cryptocurrencies in the investment field [28], [29]. Likewise, research has frequently disregarded the viewpoints of Bitcoin users [30] and the key determinants of

cryptocurrency acceptance, like risk, trust, and security, which have not received enough attention [31]. Specifically, the acceptance of cryptocurrency in investment remains largely unexplored [32], [33]. Correspondingly, policies are significant in promoting broad acceptance and utilization of new financial technology by increasing consumer confidence and awareness [34]. Thus, adopting cutting-edge technology could improve a nation's economic strength and the independence of its people, especially in emerging nations. People have yet to engage in cryptocurrency trading despite the ban. People who trade cryptocurrencies frequently use foreign brokers or more conventional techniques like sending money to broker accounts or paying cash directly to currency owners electronically. Hence, this study seeks to explore the determinants affecting the use of cryptocurrency in investment. It aims to fill existing gaps in the literature on cryptocurrency acceptance by examining investor behaviour in the context of emerging economies. To address this, the study is guided by the following objectives:

- To examine the influence of performance expectancy, social influence, facilitating conditions, awareness, security, and trust on the acceptance of cryptocurrency in investment.
- To test the moderating effect of government policy on the relationship between performance expectancy and social influence with investment acceptance.

Accordingly, the study seeks to answer the following research questions:

- What are the key factors influencing the acceptance of cryptocurrency in investment?
- Does government policy moderate the relationship between performance expectancy/social influence and cryptocurrency investment acceptance?

## II. Literature Review

The acceptance of cryptocurrencies has been of interest to several literature reviews. The technical components of understanding cryptocurrency acceptance have been the topic of one line of research. Perceived benefits and innovation traits (compatibility, observability, and trialability) impacted attitudes towards Bitcoin and the intention to accept it favourably, according to research that combined the risk-benefit concept, transaction cost theory, theory of planned behaviour, and innovation diffusion theory [35]. It was claimed that the behavioural intention to use cryptocurrency was influenced by performance expectancy, effort expectancy, and facilitating factors, according to [36], who used the UTAUT framework. In addition, another study that employed a multi-method approach found that travellers primarily weighed security, usability, and prices when deciding to use cryptocurrency [37]. Furthermore, related studies have recognised technology attachment and blockchain transparency as essential factors for fostering trust in cryptocurrency and promoting its commercial adoption among the public [38]. Scalability, transparency, privacy, credibility, and ethical issues were noted in a systematic assessment as barriers to crypto adoption [39]. Accordingly, studies on Bitcoin usage indicate they are a good choice for investors who want to increase profits while successfully lowering total risk through sensible diversification techniques.

Equally important, current research indicates that human behavioural factors significantly influence cryptocurrency acceptance. According to a comparative study that used the theory of planned behaviour as a framework, social media use influenced consumers' subjective criteria and opinions about Bitcoin, which influenced the acceptance of the cryptocurrency [40]. Similarly, another study emphasized how crucial the theory of planned behaviour is for elucidating intentions to adopt Bitcoin, with attitude, subjective norms, perceived behavioural control, and trust serving as vital motivators [41]. The fuzzy analytic hierarchy exploration assessed the importance of factors influencing Bitcoin investment. Their analysis identifies social influence as the paramount component, succeeded by favourable situations and perceived usefulness [42]. Recently, a comparable study conducted research focused on identifying factors influencing cryptocurrency within investments made by investors from Malaysia. Compatibility, trialability, ease of use, and complexity positively affected cryptocurrency adoption.

Similarly, cryptocurrencies continue to experience low acceptance in investment, and cryptocurrency awareness is frequently associated with younger generations and lower educational levels. Empirical studies investigating the acceptance of cryptocurrencies in investment are severely lacking in this area. However, the majority of research focused on the fundamental elements that affect Bitcoin adoption. On the other hand, the factors influencing the adoption of cryptocurrencies in investment have been the subject of very few studies. Therefore, this study's primary objective is to explore the underlying dynamics influencing investors' acceptance of cryptocurrencies.

Existing research about cryptocurrency acceptance continues to expand, yet several fundamental barriers still need resolution. Current research mainly examines cryptocurrency usage between peers and general usage while missing its adoption patterns in structured investment frameworks. Most previous research has been conducted in studies of technologically advanced Western economies, which has created a gap in empirical understanding regarding regulatory uncertainty and varied technological readiness between developing nations. Examining government policies' effects on individual cryptocurrency investment behaviour remains scarce in current academic research. Consequently, this study tackles these weaknesses to provide a more contextualized, policy-aware model of cryptocurrency investment acceptance. It extends the UTAUT by combining it with external variables incorporating awareness, security and trust to better model cryptocurrency investment behaviour. The study adopts government policy as a new moderating factor while integrating important external variables such as awareness, security and trust into its empirical model structure. The extension of the UTAUT model with security awareness and trust dimensions delivers a stronger policy-oriented description of cryptocurrency investment behaviours in emerging markets. Subsequently, this study establishes itself as a significant addition that completes theoretical voids while improving real-world understanding.

## III. Research Framework

The most significant determinants of behavioural intention to use technology are the UTAUT characteristics of social influence and performance expectancy [43]. Additionally, little research was carried out on concepts like social influence and conducive conditions [44]. The present study was theoretically grounded in the UTAUT paradigm. Security and awareness were added to the UTAUT model to increase its predictability [45]. Users' security concerns prompted the use of the structures. Performance expectancy, social influence, facilitating conditions, awareness, security, and trust were suggested as predictors of whether or not people would embrace cryptocurrency in investment (ACI), as shown in Fig. 1.

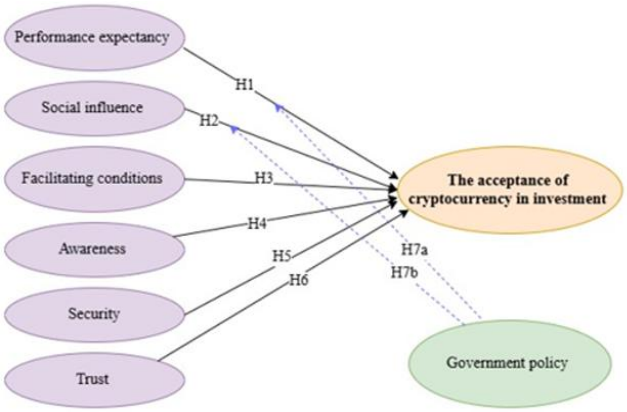


Fig. 1. Research framework.

## IV. Hypotheses Testing

### A. Performance Expectancy

Performance Expectancy (PE) is the level to which individuals believe using cryptocurrencies would help them do their jobs better [46]. Current research on cryptocurrencies indicates that performance expectancy is one important aspect influencing people's use of cryptocurrencies [47]. Cryptocurrencies are structured on the Blockchain technology. In addition to offering more advantages to users, the technology has solved the issues with traditional payment methods like PayPal and credit cards [48]. The introduction of cryptocurrencies is anticipated to increase user convenience in financial transactions. Transaction efficiency, for instance, might be improved [49]. The fund transfer procedure is improved, and transaction costs are reduced when central financial institutions are eliminated [50]. Numerous studies have found that performance expectancy robustly impacts users' behavioural intentions to use Bitcoin [51]. In this regard, performance expectancy was an important driver of behavioural intention to utilise cryptocurrencies [52]. Nonetheless, it was pointed out that performance expectancy had a detrimental effect on behavioural intention to use cryptocurrency [53]. As a result, the findings of the prior investigations contradict one another. The findings are inconclusive. Further research is needed on the relationship between performance expectancy and cryptocurrency acceptance in investment. Thus, this study hypothesises:

H1. Performance expectancy is positively related to the acceptance of cryptocurrency in investment.

### B. Social Influence

Social influence (SI) is related to the degree to which people believe that their family members and peers are influencing them to use cryptocurrencies [54]. According to earlier studies, peer groups, family members, and other current technology users' attitudes greatly impact a person's behavioural intent to use technology [55], [56]. The literature also highlights how effective word-of-mouth is at influencing people's opinions. According to several research studies, the behavioural intention to use innovation is positively influenced by social effects [57]. Similarly, [58] highlighted the impact of social influence as a motivator for users' intent to use cryptocurrency. Therefore, people's inclinations to adopt cryptocurrencies are positively impacted by social influence [58]. However, social influence was reported to have a negligible impact on the acceptance of cryptocurrencies [59]. Social influence significantly impacts consumers' intention to utilize new technology when they know little about it [60]. Since cryptocurrency is a relatively new technology, users don't know much about it. Therefore, it is anticipated that consumers' behavioural intention to embrace Bitcoin as an investment will be positively influenced by friends or loved ones' positive influence regarding the advantages of cryptocurrency. It was claimed that individuals' intentions to adopt cryptocurrencies are positively impacted by social influence [61], [62]. Thus, this study formulates:

H2. Social influence is positively related to the acceptance of cryptocurrency in investment.

### C. Facilitating Conditions

Facilitating Conditions (FC) were characterized as customers' opinions on the accessibility of the technology infrastructure and support required to embrace cryptocurrency [63]. When resources and assistance are available, people are more likely to use technology [64]. Since cryptocurrencies are a quickly developing technology, there isn't enough infrastructure or legal framework to support their use. Additionally, virtual communities centred around cryptocurrencies, such as social media groups and online forums, encourage and counsel people to embrace cryptocurrencies in their financial endeavours. According to earlier research, the conducive circumstance is among the most important predictors of cryptocurrency use intention [65]. However, it has been discovered that the acceptance of cryptocurrencies is not much impacted by facilitating conditions [66]. Consequently, this study proposes:

H3. Facilitating conditions is positively related to the acceptance of cryptocurrency in investment.

### D. Awareness

Awareness (AWAR) is described as a person's understanding of innovation and the advantages of embracing it [67]. According to this study, awareness is the degree to which consumers are aware of cryptocurrencies and their advantages. The significance of awareness in embracing technology was first examined in an innovation diffusion theory [68]. A new technology is cryptocurrency. As a result, users have a limited knowledge of the advantages of cryptocurrencies. Therefore, to increase the perception of its advantages, one must be aware of cryptocurrency services [70]. Several studies have shown that users' propensity to embrace cryptocurrencies is positively

impacted by awareness [28], [28], [33]. User acceptance in a contract may be hampered by ignorance of cryptocurrencies [24]. Thus, this study postulates:

H4. Awareness is positively related to the acceptance of cryptocurrency in investment.

### E. Security

Security (SEC) defines how safe a person feels when applying technology when they are online. People avoid using technology because they are anxious about it [39]. Transactions involving cryptocurrencies are carried out online. Potential financial loss, theft, or failure due to cybercrime may worry users [40]. Because of its security, individuals would feel more comfortable utilizing the technology, enabling it to reach its full potential as a cash substitute [41]. If people believe that cryptocurrencies are a safe form of money, they will be more inclined to utilize them [16]. Prior studies have demonstrated that security has a major impact on people's readiness to use digital currencies [17]-[20]. Similarly, a lack of security has negatively affected the desire to embrace Bitcoins as an investment [16]. As a result, more people see Bitcoin as a safe innovation, and they are more likely to apply it. Hence, the current research constructs:

H5. Security is positively related to the acceptance of cryptocurrency in investment.

### F. Trust

Trust (TR) is the readiness to trust someone or something because you think they are reliable. Trust is the belief that a system will be able to carry out all of its intended tasks. Accordingly, trust was divided into two categories: i) behavioural intentions containing ambiguity and vulnerability, and ii) faith or confidence in the reliability of another individual [47]. According to earlier studies, a person's behaviour varies based on their online purchasing confidence [33]. Due to the financial risk involved, online payment systems demand the highest confidence level [24]. Furthermore, it was found that user commitment to online transactions is increased when trust is present [32]. Furthermore, trust has been shown to predict Bitcoin use positively as a payment mechanism [28]. Thus, this study hypothesizes:

H6. Trust is positively related to the acceptance of cryptocurrency in investment.

### G. Government Policy as a Moderator

Government Policy (GP) is related to the role of the government in motivating the application and utilisation of technology [33]. Government policy can be described in this study as the role of government-related regulations covering different rules that facilitate accepting cryptocurrency in investment. It was found that government policy influences many acceptance decisions [34]. One digital technology used in financial transactions is cryptocurrency. As a result, the features of cryptocurrencies and the function of governmental regulations will determine whether or not a person accepts them. One could argue that government policy may impact how much the government facilitates, oversees, and regulates the potential utility of Bitcoin services [35]. The impact of one variable on another is either increased or decreased by a moderator variable [36]. Government policy has been shown to support people's financial choices, including accepting cryptocurrencies [37]. Government rules, however, make it less likely for consumers to choose to utilize cryptocurrencies [38]. The impact of social influence and performance expectations on adopting cryptocurrencies as investments is then anticipated to be mitigated by government policy. The following theories are investigated:

H7(a) Government policy moderates the relationship between performance expectancy and the acceptance of cryptocurrency in investment.

H7(b). Government policy moderates the relationship between social influence and the acceptance of cryptocurrency in investment.

## V. Research Methodology

### A. Data Collection

Only 220 of the 290 questionnaires designed for the sample were filled out and returned, and the study population comprises people interested in investing in cryptocurrencies. As a result, 76% of the response rate was reached. The survey aimed to collect information on respondents' knowledge of cryptocurrency's features and their propensity to embrace it in the future. This data was measured using a Likert-type scale, where, 1 represents strongly disagree, and 7 represents strongly agree. With the necessary adjustments made for the specific setting of this study, the majority of the 28 items in this section were taken from recent Bitcoin literature as well as from previous studies conducted in different situations. The second section of the questionnaire revealed information about the respondents' age, gender, and level of education. The questionnaire was designed and disseminated in English.

### B. Data Analysis and Results

The gathered data was analysed using SPSS version 29 and SEM. The recommendations of [48], [49] and earlier studies in this area served as an inspiration for the selection of these techniques. Table I shows that 61% of respondents were female and 39% of respondents were male. Regarding age grouping, 45.8% of respondents were in the 25 to 34 age range, 16.8% were in the 35 to 44 age range, 30.4% were in the 18 to 24 age range, and 7% were above 44. Sixty-three percent of the respondents had a Bachelor's degree, sixteen percent had a Diploma, six percent had Certificates, and nine percent had a Postgraduate degree.

TABLE I. Demographic Profile

| Demographics | Categories | (%) |
|---|---|---|
| *Gender* | *Male*<br>*Female* | *39*<br>*61* |
| *Age* | *18-24*<br>*25-34*<br>*35-44*<br>*44 and above* | *30.4*<br>*45.8*<br>*16.8*<br>*7.0* |
| *Educational Background* | *Certificate*<br>*Diploma*<br>*Bachelor's degree*<br>*Postgraduate degree*<br>*Others* | *6.0*<br>*16.0*<br>*63.0*<br>*9.0*<br>*6.0* |

In the same way, several crucial metrics, including nomological validity, convergent validity, discriminant validity, and face validity, were included in the analytic process to evaluate the validity and dependability of the structural model employed in the Structural Equation Modelling (SEM) technique. Convergent validity, which ensures that items evaluating a certain idea have a significant amount of common variation, was evaluated using average variance extracted (AVE), factor loadings, and reliability measures (in this case, Cronbach's alpha). Cronbach's alpha AVE and factor loadings of 0.5 or higher are deemed acceptable, whereas an AVE of 0.6 or higher is deemed acceptable by [49].

Table II indicates a high degree of internal consistency among the measures employed to measure each aspect, with Cronbach's alpha values ranging from 0.839 to 0.895. Furthermore, the AVE values, which range from 0.541 to 0.782, are greater than the 0.5 threshold, suggesting that the underlying constructs explain over 50% of the variance in the observed variables. A strong association between the latent constructs and the observable variables is also indicated by the fact that all factor loadings are higher than 0.5. Overall, these findings demonstrate that all prerequisites for convergent validity have been met, confirming the model's attainment of convergent validity. By showing that the items measuring each construct are indicative of the respective underlying constructs and share a significant amount of common variation, this validates the robustness and reliability of the measurement model.

TABLE II. CONVERGENT VALIDITY MEASURE

| Variables | Cronbach's Alpha | AVE |
|---|---|---|
| *PE* | *0.856* | *0.541* |
| *FC* | *0.864* | *0.661* |
| *SI* | *0.895* | *0.747* |
| *AWAR* | *0.869* | *0.698* |
| *SEC* | *0.874* | *0.543* |
| *TR* | *0.839* | *0.782* |
| *GP* | *0.845* | *0.785* |
| *ACI* | *0.843* | *0.786* |

The discriminant validity of each construct in the model must differ from the other constructions. Relatively, discriminant validity can be evaluated in a variety of ways. The fit indices for the baseline and limited models were then compared, with the connection between the components in this study fixed at 1. Consequently, discriminant validity is attained if there is a significant difference in the fit indicated between the two models. Table III shows that the baseline model's Chi-square (x2) value was 1,449.196 with 643 degrees of freedom, while the limited models' x2 value was 1,607.716 with 545 degrees of freedom (DF). This shows a difference in the degree of freedom of seven and an x2 difference of 1,229.197. The fit indices for the restricted models and baseline models differ dramatically. Accordingly, this model attains discriminant validity, and consulting experts in this field verified the face and nomological validity. Lastly, the findings exposed that the comparative fit index (CFI) is 0.839, and its root mean square error of approximation (RMSEA) is 0.541. For both measures, these levels are acceptable [44], [47], [50]. Therefore, this validates the model as a whole.

TABLE III. DISCRIMINANT VALIDITY MEASURES

| Elements | Chi-square | DF |
|---|---|---|
| *Baseline model* | *1,449.196* | *643* |
| *Restricted model* | *1,607.716* | *638* |
| *Changes* | *158.520* | *5* |

## VI. RESEARCH HYPOTHESES

The hypotheses discussed above are tested through path analysis, as shown in Table IV. The findings illustrated that performance expectancy significantly impacts individuals' acceptance of cryptocurrency in investment. Consequently, Hypothesis 1 is supported ($\beta = 0.052$, $t = 1.142$, $p = 0.127$). This result indicates that the ease associated with cryptocurrency will allow users to accept cryptocurrency when investing. This is supported by [15], who stated that behavioural intention to utilise cryptocurrency is hindered when cryptocurrency is difficult. Moreover, social influence significantly affects an individual's behaviour in accepting cryptocurrency in investment. Thus, hypothesis H2 is supported ($\beta = 0.099$, $t = 2.339$, $p = 0.010$). The results concurred with those of [35], [36], who revealed that behavioural intent toward cryptocurrency acceptance among Saudi Arabian university students is influenced by the views of near and loved ones, such as friends and family, regarding the advantages of cryptocurrencies. Additionally, it was shown that facilitating conditions substantially impacted the adoption of cryptocurrencies in investment. Consequently, ($\beta = 0.101$, $t = 2.116$, $p = 0.017$) support Hypothesis 3. This result is consistent with [20]. It refers to the political climate, the government's desire to encourage the use of cryptocurrencies in investing, and the laws, circulars, and policies that have been put in place to assist cryptocurrency acceptance.

TABLE IV. REGRESSION RESULTS

| Hypothesis | Relationship | ß | T Values | p Values | Result |
|---|---|---|---|---|---|
| *H1* | *PE -> ACI* | *0.052* | *1.142* | *0.127**** | *Supported* |
| *H2* | *SI -> ACI* | *0.101* | *2.116* | *0.017**** | *Supported* |
| *H3* | *FC -> ACI* | *0.099* | *2.339* | *0.010**** | *Supported* |
| *H4* | *AWAR -> ACI* | *0.098* | *2.258* | *0.012**** | *Supported* |
| *H5* | *SEC -> ACI* | *0.276* | *5.775* | *0.05* | *Supported* |
| *H6* | *TR -> ACI* | *0.054* | *1.034* | *0.015*** | *Unsupported* |

Note. ***indicates a significant level at $p < 0.01$.,**indicates a significant level at $p < 0.05$.

All of these characteristics have a major impact on people's decision to embrace cryptocurrencies as an investment. Similarly, people who accept Bitcoin investments were found to be significantly impacted by awareness. Since (β = 0.098, t = 2.258, and p = 0.012), Hypothesis 4 is accepted. This outcome is consistent with [11], who claimed that knowledge and awareness of cryptocurrencies significantly impacted their use. The respondents' ability to obtain general information on cryptocurrencies, including their advantages and potential risks, is a noteworthy indication of awareness.

Regarding the acceptability of cryptocurrencies in investing, the respondents noted a high degree of awareness and expertise, which has positively affected their views of and acceptance of cryptocurrency in investment. Further, security was recognised to significantly affect individuals accepting cryptocurrency in investment. Accordingly, H5 is supported (β = 0.0276, t = 5.775, p = 0.05). This outcome is consistent with Almarashdeh [19], who emphasized users' perceived concerns about the security of financial transactions associated with Bitcoin use.

Nevertheless, trust was found to have no discernible effect on people's behaviour regarding the acceptance of cryptocurrencies in investment, which is contradicted by [8], [9], who noted that users are more likely to trust a currency issued by an authority than a cryptographic currency. As a result, Hypothesis 6 is rejected (β = 0.054, t = 1.034, p = 0.015) in this study for several reasons, including the decentralized nature of the cryptocurrency market, the absence of a central authority in charge of issuance, and the fact that using a reliable third party when transferring money online is not necessary [14]. The findings summarised other determinants rather than trust that could impact individuals who accept cryptocurrency in investments.

Table V shows that the relationship between performance expectancy and the acceptance of cryptocurrencies as an investment is considerably impacted by government regulation. Hypothesis 7a is thus supported (β=0.084, t=2.137, p=0.017). This suggests that government policies significantly shape the influence of performance expectations on the acceptance of cryptocurrencies in investment. This illustrates that the association between performance expectancy and accepting cryptocurrency in investment is strengthened by government policy. This finding could be further explained by the prospect theory, which claims that people make decisions based on how options are framed and are receptive to losses rather than profits [51]. In cryptocurrency, investors who expect positive returns and have high-performance expectations may be more inclined to invest [52]. If considered beneficial in lowering volatility and safeguarding investors, government policy, individuals with high-performance expectancy (positive return expectations) might be more likely to invest [53]. Government policies could enhance this positive perception if perceived as effective in reducing volatility and protecting investors [54]. This would make investors more open to the possible benefits of cryptocurrency, especially in light of restrictions, which could reinforce the positive link between the acceptance of cryptocurrency in investment and performance expectancy [55]. Finally, government policy negatively affected the correlation between SI and the acceptance of crypto in investing.

TABLE V. RESULTS OF GOVERNMENT POLICY ANALYSIS

| Hypothesis | Relationship | ß | T Values | p Values | Result |
|---|---|---|---|---|---|
| *H7a* | *PE > GP* | *0.084* | *2.137* | *0.017*** | *Positively Supported* |
| *H7b* | *SI > GP* | *-0.080* | *1.908* | *0.028*** | *Negatively Supported* |

*Note. **indicates a significant level at p < 0.05.*

Hypothesis 7b is therefore not supported (β=-0.080, t=1.908, p=0.028). Consequently, the analysis's findings show a negative correlation between social impact and investors' acceptance of cryptocurrencies. This illustrates how the presence of governmental regulation may mitigate the relationship between social influence and the adoption of cryptocurrencies as investments. This finding could be explained by Social Learning Theory [56], which posits that individuals learn by observing and imitating others' behaviours. Regarding cryptocurrency, individuals may be persuaded to invest due to the influence of friends, family, or online communities. However, government policy can introduce uncertainty and complexity to the process, making investors less likely to follow the actions of others [60] mindlessly. They might be more cautious and conduct their research before investing, weakening the direct influence of social pressure. The additional justification that may align with this outcome is related to Uncertainty Reduction Theory, which theorises that individuals seek to reduce uncertainty in situations involving risk [58]. Concerning cryptocurrency, a new and complex investment, individuals might rely heavily on social influence to make decisions. Nevertheless, when governments establish policies, it provides a sense of legitimacy and clarity, potentially reducing the reliance on social cues and leading to more independent decision-making.

## VII. DISCUSSION

Using SEM analysis, this study aimed to investigate the factors influencing the adoption of cryptocurrencies in investments. The results showed that users' adoption of cryptocurrencies as an investment is positively impacted by several elements, which aligns with many previous studies. These include performance expectancy [47]-[48], facilitating conditions [63], social influence [55]-[56], and awareness [67]. However, the acceptance of cryptocurrencies was not much impacted by trust, which has failed to be replicated in past studies [28], [32], [69]. Conceptual hurdles exist in cryptocurrency because its decentralized and pseudonymous systems function without standard trust components like banks or regulators. This can probably be explained by Gunawan and Achmad [39], who noted that new users of decentralized platforms face challenges due to the absence of trusted identifiable entities on these platforms.

## VIII. CONCLUSION

The insights obtained by this study hold considerable value for practitioners, academics, and policymakers, shedding light on aspects of cryptocurrency in investment behaviour that may not align with users' cultural and social values. Consequently, the findings contribute to gaining a deeper comprehension of the dynamics of cryptocurrency acceptance. The study's findings also serves as a basis for promoting user involvement with cryptocurrencies for financial investment. This study explores a topic that has not been experimentally investigated before using

the UTAUT model in a new setting. Furthermore, this study offers practitioners and regulators information on crucial elements to encourage cryptocurrency investment and adoption among stakeholders. Cryptocurrencies and similar digital assets offer the potential for more efficient exchange methods than traditional currencies, highlighting the need for further investigation. With swift progressions in financial innovation, fiscal advisors and users should remain current regarding the latest developments in both knowledge and skills. Traditional financial institutions face a serious challenge if they do not adjust to these changes. Users can choose alternative advice platforms that offer more effective, flexible, and affordable services. The results might also lead people to consider cryptocurrencies a good investment choice.

## IX. Limitations and Future Research

It is essential to consider this study's various possible limitations. First, a self-report survey and cross-sectional research design may restrict causal inferences and miss gradual changes over time [69]. Future research could use experimental designs to overcome this restriction. Second, a complete collection of factors impacting the adoption of cryptocurrencies in investment is not included in the study's suggested model. Consequently, this model needs to be seen as a starting point for additional study in order to create a more thorough understanding of cryptocurrency acceptance in investment. Since many users engage with cryptocurrencies as investment assets, future research would benefit from incorporating inherent features and risks specific to cryptocurrency in investment, such as traceability, price value, and sustainability, and examining their influence on user attitudes toward cryptocurrency acceptance.

Thirdly, although structural equation modelling (SEM) was used in this investigation, alternative theoretical perspectives and methodological approaches could produce additional insights, potentially enriching our understanding of the phenomenon. Lastly, longitudinal research on cryptocurrency adoption could offer valuable perspectives on the evolving dynamics of acceptance behaviour, particularly as it responds to shifts in market trends, regulatory developments, and technological advancements. By addressing these shortcomings, future studies could advance a more sophisticated comprehension of cryptocurrency investment behaviour and its wider ramifications for stakeholders and international financial markets.

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# Healthy and Unhealthy Oil Palm Tree Detection Using Deep Learning Method

Kang Hean Heng[1], Azman Ab Malik[2], Mohd Azam Bin Osman[3], Yusri Yusop[4], Irni Hamiza Hamzah[5]
School of Computer Science, Universiti Sains Malaysia, 11800 USM, Gelugor, Malaysia[1, 2, 3]
Environmental Technology, Universiti Sains Malaysia, School of Industrial Technology, 11800 USM,Gelugor, Malaysia[4]
Cawangan Pulau Pinang, Universiti Teknologi MARA, Electrical Engineering Studies, College of Engineering, 13500 Pulau Pinang, Malaysia[5]

***Abstract*—Oil palm trees are the world's most efficient and economically productive oil bearing crop. It can be processed into components needed in various products, such as beauty products and biofuel. In Malaysia, the oil palm industry contributes around 2.2% annually to the nation's GDP. The continuous surge in demand for oil palm worldwide has created an awareness among the local plantation owner to apply more monitoring standards on the trees to increase their yield. However, Malaysia's cultivation and monitoring process still mainly depends on the labor force, which caused it to be inefficient and expensive. This scenario served as a motivation for the owner to innovate the tree monitoring process through the use of computer vision techniques. This paper aims to develop an object detection model to differentiate healthy and unhealthy oil palm trees through aerial images collected through a drone on an oil palm plantation. Different pre-trained models, such as Faster R-CNN (Region-Based Convolutional Neural Network) and SSD (Single-Shot MultiBox Detector), with different backbone modules, such as ResNet, Inception, and Hourglass, are used on the images of palm leaves. A comparison will then be made to select the best model based on the AP and AR of various scales and total loss to differentiate healthy and unhealthy oil palm. Eventually, the Faster R-CNN ResNet101 FPN model performed the best among the models, with AParea = all of 0.355, ARarea = all of 0.44, and total loss of 0.2296**

***Keywords*—Component oil palm detection; deep learning models; object detection; Faster R-CNN; drone imagery analysis***

## I. INTRODUCTION

Palm oil is the most productive oil crop and can be processed into various products, such as soap, vegetable oil, beauty products, etc. In Malaysia, palm oil has been regarded as Malaysia's golden crop. The oil palm industry has always been one of the most important agricultural exports for the nation. In 2022 alone, palm oil contributed 66.1% of the nation's total export earnings, which amounted to MYR 44.63 billion this year [1]. Besides, the demand for palm oil continues to surge due to the growing population and the shortage of sunflower and rapeseed oils in recent years. It is estimated that the annual production will be quadrupled, reaching 240m tons by 2050 [2]. To benefit from this scenario, Malaysia's oil palm industry has to be able to increase its yield. As a result, the monitoring process of oil palm trees has become important to ensure a continuous supply of palm oil.

One of the main focus or projects involves differentiating and detecting healthy and unhealthy oil palms in the plantation. This task is particularly important because insects can transmit the disease affecting an oil palm tree to its surrounding trees. Also, it is important to provide timely treatment to the infected unhealthy oil palm trees.

However, the problem for the Malaysian oil palm industry has always been labor shortages as it heavily depends on foreign labor to carry out the monitoring task. Nevertheless, the situation worsened when coronavirus hit the globe in early 2020, which caused the border between countries to close. Foreign laborers are not able to enter Malaysia to fulfill the labor shortage faced by the industry. Fortunately, this crisis has successfully prompted the industry player to innovate and implement some automation, such as object detection techniques, to overcome the problem. With object detection techniques put in place, it can help the plantation owners to shorten the time in detecting unhealthy and healthy oil palm trees, thus increasing the efficiency of the task as the traditional way of oil palm tree monitoring is too labor-intensive and inefficient. Once this project is successful, it will provide a reference for other researchers to improvise further and develop the detection model. Besides, it also acts as a starting point for the companies in this industry to utilize this method to overcome the labor shortage, further helping them increase their crop yield moving forward. Lastly, it is also believed that this project can help to share awareness and gather the attention of other companies of different crops, apart from oil palm, to utilize the object detection technique in their crop plantation and management process.

Object detection is an important computer vision task that detects instances of visual objects of a particular class (such as humans, animals, or cars) in digital images [3]. The idea and early design of object detection started in the 1900s. In recent years, the evolution of GPU architecture and deep learning techniques have generalized the usage of object detection techniques in many sectors. Autonomous driving, defect detection, and traffic monitoring are real-world applications that use object detection models. There are two types of object detection frameworks, which are region-based, and regression/classification based. Region-based frameworks are commonly referred to as two-stage detectors, while regression/classification-based frameworks are referred to as one-stage detectors.

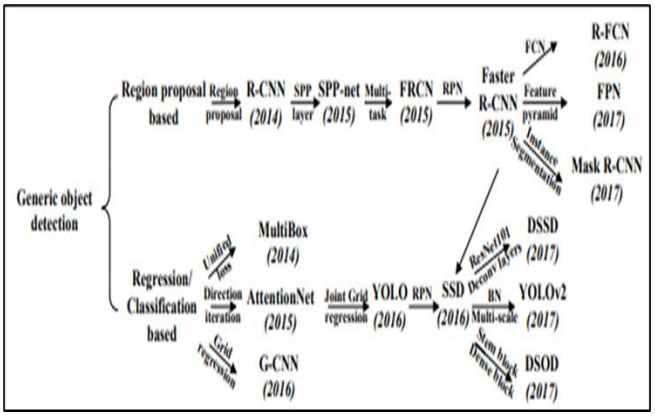


Fig. 1. Development of object detection frameworks [4].

Two-stage detectors will first generate region-based proposals, then classify each proposal into different classes. The typical examples of two-stage detectors are R-CNN, SPP-Net, Faster R-CNN, and FPN. Meanwhile, one stage detectors view object detection as a regression or classification problem, adopting a unified framework to achieve final results (categories and locations) directly [4]. Single-shot MultiBox Detector (SSD), You Only Live Once (YOLO), and CenterNet are some of the models that use regression/classification-based frameworks. Fig. 1 summarizes the development of two object detection frameworks.

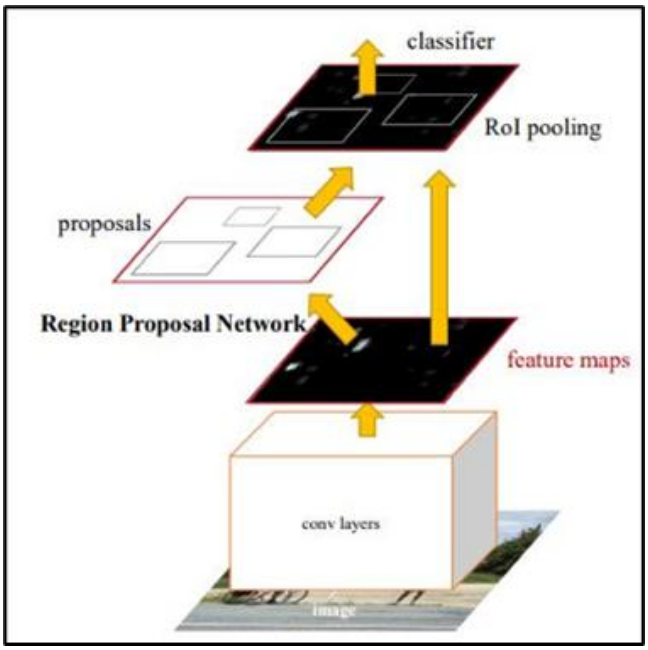


Fig. 2. RPN module [5].

Faster R-CNN is the abbreviation of Faster Region-based Convolutional Neural Network. It combines the algorithm of RPN (Region Proposal Network) and Fast R-CNN as shown in Fig. 2. It can be viewed as an updated version of Fast R-CNN, where, RPN replaces the Selective Search method. RPN is a fully convolutional network, which slides over the convolutional feature map and simultaneously predicts object boundary and object-ness scores at each position [4]. As a result, the model performs better in speed and accuracy and consumes fewer computational resources. In a paper published in [6], the authors applied Faster R-CNN on high resolution imagery for automatic detection and health classification of oil palm trees. There are two backbones selected for Faster R-CNN, which are ResNet-50 and VGG 16. The model with ResNet-50 as the backbone obtained F1 scores of 95.09%, 92.07%, and 86.96%, respectively, for oil palm tree detection, healthy tree identification, and unhealthy tree identification. Overall, the ResNet-50 model yielded a better F1 score than the VGG-16 model.

RetinaNet is a one-stage object detection model first published in a paper by Lin et al. The development of RetinaNet is aimed at overcoming the problem of class imbalance and robust estimation in Single-Shot MultiBox Detector (SSD) during training by utilizing a focal loss function. Class imbalance problem in SSD leads to many easy negatives appearing when the detector is evaluating the object locations, overwhelming the loss function and causing a degeneration in the model performance. With focal loss function, it helps to down-weight those easy negatives and thus focus training on hard negatives as shown in Fig. 3.

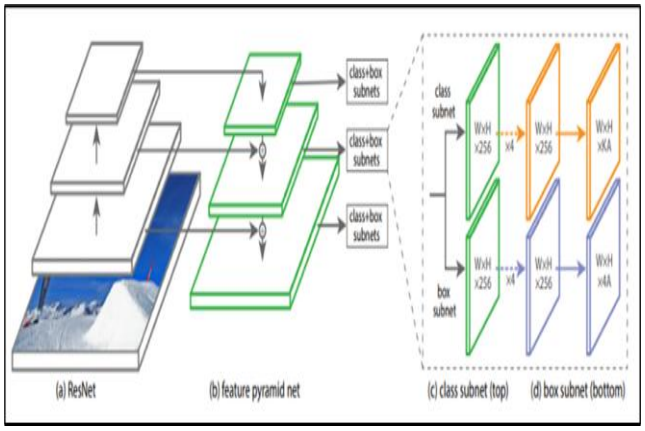


Fig. 3. RetinaNet architecture [7].

An optimized palm tree inventory model based on a RetinaNet object detector and high-resolution RGB images is proposed in 2021 to classify and locate palm trees in different scenes with different appearances and ages [8]. The dataset has a spatial resolution of 25cm. The detection model for palm tree inventory achieved a precision of 89.3% on the validation dataset and 76.9% on the test dataset. Both precision values are on the mAP@IoU = 0.50 category. CenterNet is an anchorless object detection model published [9], entitled "Objects as Points" in 2019. The idea of anchorless in this model is to replace Non-Maximum Suppression (NMS) algorithm used in SSD or YOLO. NMS algorithm functions as a filter to select one single bounding box out of the many overlapping bounding boxes in the post process. For example, YOLOv3 generates more than 7k bounding boxes in its prediction for each image, mostly considered garbage predictions, and the NMS algorithm will need to run pairwise checks for those overlapping bounding boxes [10]. Fig. 4 shows a CenterNet algorithm. This method increases the complexity of the model when the number of bounding boxes (predictions) increases. It also forces the model to consume more computational power and time in clearing those irrelevant predictions.

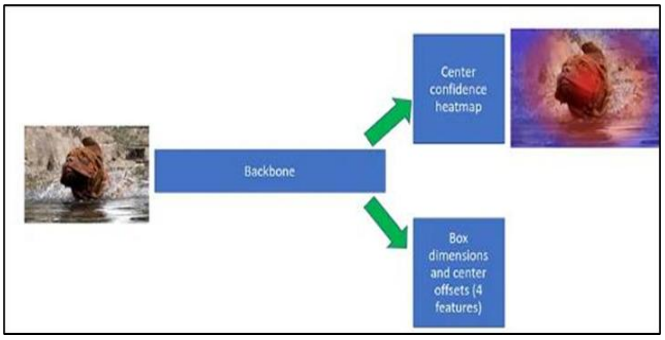


Fig. 4. CenterNet algorithm [10].

Meanwhile, CenterNet predicts a box center for an object and uses the center point to regress the value for its box dimensions and offsets, directly removing irrelevant predictions without any decoding process. An anchor-free deep learning model, CenterNet, is used to detect individual crown locations and regions from dense 3D terrestrial laser scans [11]. There are 1181 crowns from twelve plots. The author used eight plots for training, and four plots for testing. The model is trained over 40k iterations. The maximum training F1-score and IoU were 0.881 and 0.670, while testing result showed a F1-score of 0.754 and IoU of 0.583. The result also showed that a taller, larger, smoother, less crowded, and less overlapped tree was found easier to be detected by the model. Table I shows a comparison of object detection models for two stage and one stage of model. ResNet, Inception, and HourGlass Network are all convolutional neural networks widely used for image classification tasks. However, each contains its design specification to optimize the deep neural network as it goes deeper.

TABLE I. COMPARISON OF OBJECT DETECTION MODELS

| Model | | Innovations | Strength | Limitations |
|---|---|---|---|---|
| Two Stage | Faster R CNN | The RPN module helps to generate high-quality region proposals and saves time compared to the Selective Search method. | Higher accuracy | Complicated training with high memory consumption |
| One Stage | RetinaNet | Focal loss function – down weight the easy negatives and focus on hard negatives | Stable training for class imbalance | Lower accuracy compared to a two-stage detector |

Before ResNet was invented, researchers tended to design deep learning networks by increasing their layers and depth as shown in Fig. 5. However, it comes to a limitation where the train and test errors increase when it goes even deeper. In a paper published by [12], it is believed that this degradation in performance is not caused by overfitting, and indicated that not all networks could be optimized easily by making it deeper. As a result, a deep residual learning framework has been proposed by [12] to address the degradation problem. ResNet learns residual functions with reference to the layer inputs instead of learning unreferenced functions. Thus, it makes it possible to train a much deeper network while minimizing the error value.

Next, Inception Network as shown in Fig. 6 is designed to decrease the computational cost and burden to run a deep neural network. Besides, it also helps to better optimize parallel computing. The network performs max pooling and a convolution on an input with three different sizes of filters (1x1, 3x3, and 5x5), rather than stacking them in sequence. As the network progress, it will grow wider and not deeper. This also help to reduce vanishing gradient problem [14]. Meanwhile, HourGlass Network consists of multiple stacked hourglass modules, which allow for repeated bottom-up, top-down inference [15]. It is specially designed for predicting human poses. The advantage of this network is that it captures and consolidates information across all scales of the image [15].

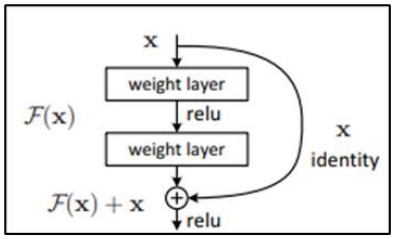


Fig. 5. Residual learning [12].

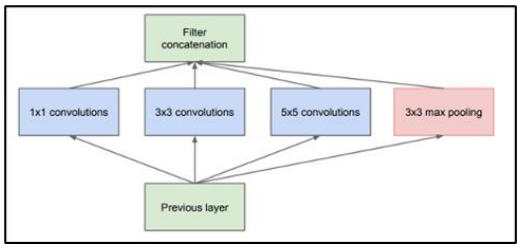


Fig. 6. Inception module [13].

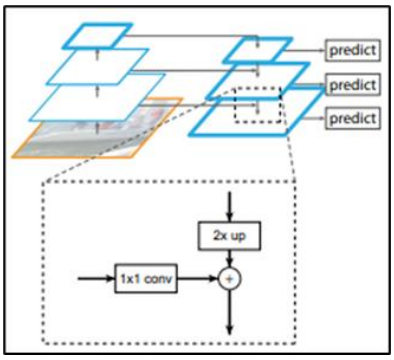


Fig. 7. Building block of FPN [16].

The Feature Pyramid Network is published by Lin et al. in 2017. FPN can be seen as an updated version of ConvNet's pyramidal feature hierarchy. FPN takes a single-scale image of an arbitrary size as input, and outputs proportionally sized feature maps at multiple levels, in a fully convolutional fashion. This process is independent of the backbone convolutional architecture [16]. As shown in Fig. 7, the building block involves a bottom-up pathway, a top-down pathway, and lateral connections. The result from the paper showed that average precision of a Faster R-CNN ResNet50 with FPN, goes up by 7.6%, from 26.3% to 33.9%. The evaluation of the model is made on COCO minival set.

A standard implementation, which can be used as a benchmark among different datasets is published in 2020. One of the famous metrics used for model evaluation is called average precision (AP) and average recall (AR). Before going deeper into how metrics works, it is also wise to understand the concept of intersection over union (IOU). It is a measurement based on Jaccard Index, a coefficient of similarity for two sets of data [17]. For object detection model, IOU measures the overlapped area between two bounding boxes, one from prediction, and one of ground-truth, divided by the area of union between them. With a given threshold, if the IOU is bigger than the threshold, then the detection is considered valid and vice versa. With IOU in place, AP and AR can be evaluated in different variations as mentioned in Table II.

TABLE II. PERFORMANCE METRICS [17]

| Metrics | Meaning |
|---|---|
| AP@50:5:95 | AP of 10 IOUs varying from range of 50% to 95% with steps of 5%. |
| AP50 | AP of IOU of 50% |
| AP75 | AP of IOU of 75% |
| AP-S | AP for small sized objects (area < 322 pixels) |
| AP-M | AP for medium sized objects (322 < area < 962 pixels) |
| AP-L | AP for large sized objects (area > 962 pixels) |
| AR@50:5:95 | AR of 10 IOUs varying from range of 50% to 95% with steps of 5%. |
| AR-S | AR for small sized objects (area < 322 pixels) |
| AR-M | AR for medium sized objects (322 < area < 962 pixels) |
| AR-L | AR for large sized objects (area > 962 pixels) |

The loss function is a common but essential metric in deep learning. It provides a numerical representation of how well a model performs on a particular task. It helps the researchers to evaluate and fine-tune the model to achieve a better result. If the model predicts poorly, the loss function will output a higher number and vice versa. In object detection, the loss function can be categorized into two parts; one is classification loss, another one is localization loss. The former is applied to train the classification head for determining the target object type, and the latter is used to train another head for regressing a rectangular box to locate the target object [18]. Once these two categories adds on, it is called a total loss for the object detection model.

## II. RESEARCH METHOD

A standard object detection workflow has been presented to create a deep learning-based object detector in a paper published in [19] and the workflow as shown in Fig. 8. The workflow starts with the dataset acquisition process, followed by data annotation. The images will then be augmented into different sizes and split into training and test sets according to a selected ratio. Next, the training and test set will be fitted and trained in an object detection algorithm. Once the training is done, the best model will be saved. Finally, the best model will be used to infer the test dataset or new images for evaluation purposes. The evaluation process will be based on the selected metrics, such as mAP, AP, and AR. If the model performs well, it can be deployed into a real-case scenario.

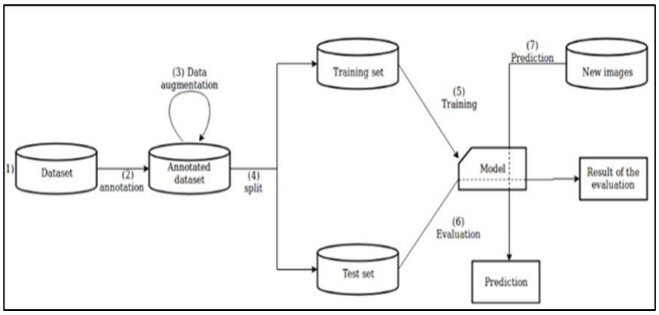


Fig. 8. Workflow for object detection project [19].

Fig. 9 illustrates the overall lifecycle of the object detection project, and it will only cover performance evaluation. The model's deployment for real-case scenarios will depend on the client's needs. The cycle consists of 6 stages: problem understanding, data collection, data annotation and augmentation, data transformation, modelling, and model evaluation. During the early stage of the problem understanding, one discussion session was held with the client, and the problem faced was identified. The problem is due to the client's lack of domain knowledge to develop a proper object detection model. Next, several meetings were held to discuss the desired outcome and expectations from the client. The goal was then set: to develop a prototype model which can make a good prediction on healthy and unhealthy oil palm trees on aerial images captured by drone.

The next stage in the project lifecycle is data collection. It is also known as data acquisition in the object detection workflow. The client provides the image dataset for this project. It consists of 90 images, which are collected from an oil palm plantation in Perak, based on the coordination stored in the metadata of the image. The images are collected during sunny and cloudy weather with different aerial angles. Multiple trees can be seen in an image with tree crowns overlapping each other. Some are unhealthy trees as shown in Fig. 10, and some are healthy trees as shown on Fig. 11. The health of the oil palm trees can be differentiated using crown color. Most healthy trees have green crowns, while the unhealthy ones tend to have yellow and brown crowns [20]. All the images are captured through a drone and stored in 32-bit PNG format. The image size ranges from 8 MB to 12 MB, while the image size is fixed at 2982-pixel x 1694-pixel. All the images have a resolution of 144 dots per inch (DPI).

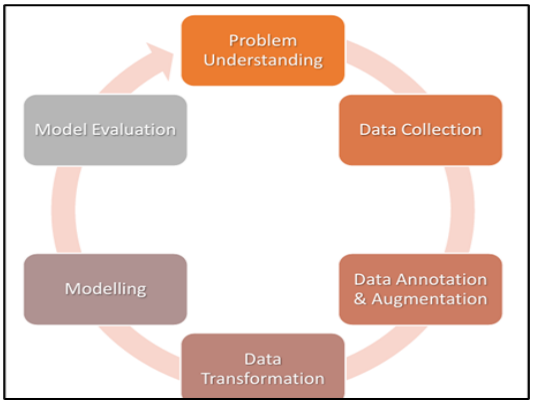


Fig. 9. Project lifecycle.

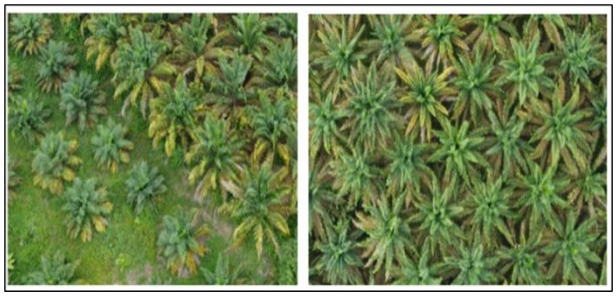

Fig. 10. Tree crown of unhealthy oil palm tree.

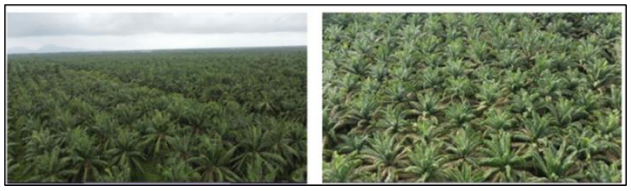

Fig. 11. Tree crown of healthy oil palm tree.

Next, the images were manually annotated using an open-source tool called 'Labellmg' as shown in Fig. 12. The software is written in Python format and uses Qt for its graphical interface [21]. The bounding box was drawn on the visible objects. Each bounding box represents the object's coordinate in the image with four axis: xmin, xmax, ymin, and ymax. Two classes, 'Healthy' and 'Unhealthy', are used to annotate each object in the images. The annotations are saved in Pascal VOC XML format.

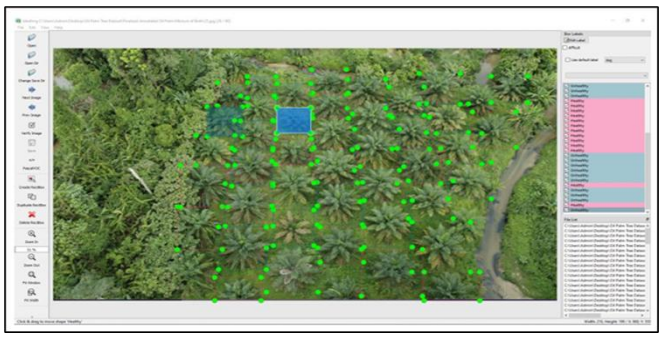

Fig. 12. LabelImg.

The images were once trained using one of the selected object detection models. However, the image size is too big for the GPU to handle. The GPU on Google Colab is the Nvidia Tesla T4, which has 16GB of memory. As a result, the images must be rescaled and reduced in size. The images were augmented or rescaled to 1024 x 1024 pixels. The bounding boxes also shrank according to the rescale ratio using a python script found in a GitHub repository. Italo José codes the script [22].

The image dataset is then split randomly into training and validation sets with a ratio of 8:2 as shown in Fig. 13. Once the splitting process is complete, the respective annotations are split into two folders, training and validation set accordingly. The dataset will need to train in different models. Some models are stored in different model zoos of different platforms, such as TensorFlow, PyTorch, and Detectron2. The model zoo is a repository where companies or open-source institutions store machine learning and deep learning models. Object detection models, stored in TensorFlow and PyTorch model zoo, are developed by Google and Linux Foundation (previously Meta AI). Those models are trained on the PASCAL VOC dataset, and the annotation needs to be in XML format. Meanwhile, models in the Detectron2 platform are maintained by Meta AI, and the models are trained on the COCO dataset. Thus, the annotation needs to be in JSON format. As a result, the annotations in XML format are converted into JSON format using a script found in the GitHub repository. A person develops the script with a pseudonym called fam_taro [23]. Meanwhile, a script developed by Dat Tran in GitHub is being used to generate TFRecord format for TensorFlow object detection models [24]. The Fig. 14 shows the dataset directory structure for the project.

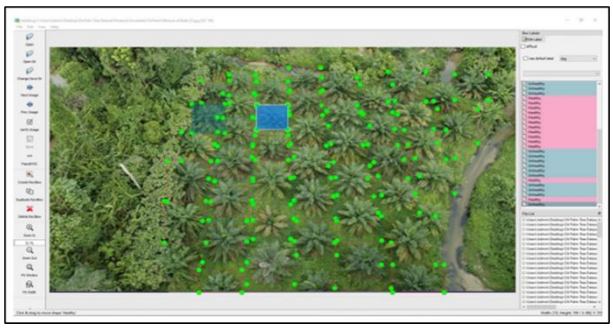

Fig. 13. Original size image vs resized image.

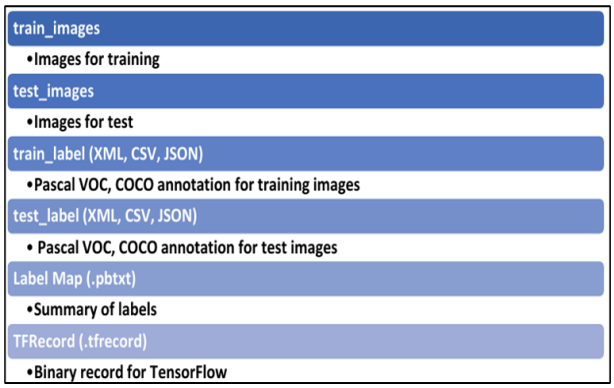


Fig. 14. Dataset directory structure.

TABLE III. MODEL SPECIFICATION

| Specification | Faster R-CNN | | RetinaNet | | CenterNet |
|---|---|---|---|---|---|
| Model Zoo | TensorFlow | Detectron2 | TensorFlow | Detectron2 | TensorFlow |
| Annotation Format | XML | JSON | XML, | JSON | XML |
| Backbone | Inception-ResNet | ResNet-50/101 | ResNet-50/101 | | HourGlass |
| FPN | No | Yes | Yes | | No |
| Anchor | Yes | | Yes | | No |
| Input Image Size | 640 x 640 | | 640 x 640 | | 512 x 512 |

Several models are being selected for training. The justification of the advantages and disadvantages of each model is written in previous discussion. Table III summarizes the specification of the selected models.

Besides, several settings need to be configured in the config file of each model before the training process starts. Table IV summarizes the basic settings in the config file.

TABLE IV. CONFIG SETTINGS

| Settings | Options |
|---|---|
| num_classes | 2/3* |
| Path to train_images/ test_images/ labelmap | Path to the working directory in Google Drive |
| fine_tune_checkpoint | Checkpoint of pre-trained model downloaded from the model zoo of the respective platform |
| fine_tune_checkpoint_type | Detection |
| batch_size | 2/4 |
| num_steps/iter/epoch | 50000/3600/100 |

Many pre-trained object detection models are available in the model zoo of different platforms. However, every platform requires a library version to be installed before the model can be trained on the custom dataset. In addition, the TensorFlow library, Colab, and Drive are all developed by Google. As a beginner, it is reasonable to consider models from the TensorFlow library as the first choice due to compatibility issues. Unfortunately, TensorFlow models are computationally expensive to train and consume much time. A Faster R-CNN model took up to 9 hours to train. Due to cost concerns, other alternatives, such as PyTorch's TorchVision library and Detectron2 library, are being considered. The models in PyTorch take much lesser time and are easier to train. PyTorch's Faster R-CNN model only took an hour to train on the same model. However, only a limited variety of models are available to train on the platform, which is the main disadvantage of the PyTorch platform.

For Detectron2 library, it contains a variety of models that are available for training. Most models are trained with the 3x schedule (~37 COCO epochs). A Faster R-CNN model only takes an hour to train on the same dataset. It has much more model variation and consumes less time in training. As a result, the Detectron2 library is selected for the rest of the training process to produce a standardized result.

Object detection has recently been deemed feasible due to the rapid development of GPU parallel computing. GPU parallel computing allows the model to split the training process into thousands of tasks and process it simultaneously. It is much more efficient and timesaving than the CPU, which only processes one task simultaneously. Unfortunately, there is no GPU hardware available on the laptop. Specification of project setup as shown in Table V. One of the alternatives available online is the Cloud GPU Platform. Some examples of these platforms are Google Colaboratory, Paperspace, Microsoft Azure, and Kaggle.

In order to stay competitive, every platform offers similar GPU devices and only differs by the subscription plan. As a result, it is really up to user preferences and usage. For this project, Google Colaboratory has been selected due to several reasons. The user interface is also not much different from Jupyter Notebook. Lastly, it allows the users to link to their Google Cloud storage, keeping the whole process on the cloud. Thus, it is easier and more flexible for beginners and students.

TABLE V. SPECIFICATION OF PROJECT SETUP

| Types | Specification |
|---|---|
| CPU | Nvidia Tesla T4 (16GB memory) |
| Storage | Google Drive (100GB) |
| IDE | Google Colab (Python) |
| RAM/ Disk Space | 12.7 GB/ 107.7 GB |

## III. RESULTS AND DISCUSSION

The models selected are CenterNet HourGlass104 512x512 and Faster R-CNN Inception ResNet V2 640x640. The basic settings of the model as shown in Table VI and Table VII, the results, and the inference images as shown in Fig. 15 and Fig. 16.

TABLE VI. BASIC SETTINGS FOR TENSORFLOW MODELS

| Settings | Options |
|---|---|
| num_classes | 2 |
| fine_tune_checkpoint_type | Detection |
| batch_size | 2 |
| num_steps | 50000 |

TABLE VII. RESULT FOR CENTERNET & FASTER R-CNN

| Model | CenterNet HourGlass104 512x512 | Faster R-CNN Inception ResNet V2 640x640 |
|---|---|---|
| Average Precision (AP) @ [IoU-0.50:0.95 \| area= all] | 0.372 | 0.351 |
| Average Precision (AP) @ [IoU=0.50:0.95 \| area= small] | -1 | -1 |
| Average Precision (AP) @ [IoU=0.50:0.95 \| area= medium] | 0.194 | 0.157 |
| Average Precision (AP) @ [IoU=0.50:0.95 \| area= large] | 0.408 | 0.405 |
| Average Recall (AR) @ [IoU=0.50:0.95 \| area= all] | 0.542 | 0.475 |
| Average Recall (AR) @ [IoU=0.50:0.95 \| area= small] | -1 | -1 |
| Average Recall (AR) @ [IoU=0.50:0.95 \| area= medium] | 0.366 | 0 275 |
| Average Recall (AR) @ [IoU=0.50:0.95 \| area= large] | 0.576 | 0.516 |
| Total Loss | 5.196 | 1.788 |

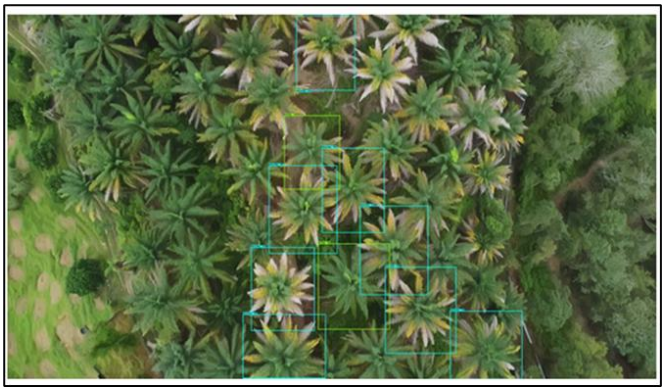

Fig. 15. Inference image of centernet hourglass104.

Fig. 16. Inference image of faster R-CNN inception ResNet V2.

In this evaluation, the inference image is a new test image with an image size of 3840 x 2160 pixels. In the image, most of the oil palm trees are considered medium or large objects, as the area of the big tree crown is above 962 pixels, and the medium one is around 322 and 962 pixels. In Table VI, the evaluation metrics shows that CenterNet with HourGlass104 backbone achieved a higher average precision (AP) for all, medium and large area categories, compared to Faster R-CNN with Inception ResNet backbone. A higher value of AP indicates that when the algorithm detects an object as healthy or unhealthy, it has a high possibility that it is correct. Furthermore, the metrics also show that the average recall rate (AR) of all, medium, and large area categories are higher in the CenterNet model than in the Faster R-CNN model. It means that the CenterNet model has fewer false negative predictions. Meanwhile, there are no small tree crowns under 322 pixels in the image that can be detected. Thus, the metrics show a value of 1 in both AP and AR for the small area category. Lastly, CenterNet achieved 5.196 in total loss, while the Faster R-CNN model only achieved 1.788. This problem can be seen in the inference image as well. Many tree crowns are left undetected in CenterNet's inference image, compared to the one in the Faster R-CNN model. This scenario also means that the CenterNet failed to predict many tree crowns, which means fewer false negative instances are being predicted (higher AR). However, those predicted ones are highly likely to be correct (higher AP). Thus, the metrics proved that the CenterNet model is not robust enough to locate the tree crowns and has a high localization loss compared to Faster R- CNN. In conclusion, both models did not produce a satisfactory result and took a very long time to train around 5 hours. As a result, a decision has been made to stop the training process for other TensorFlow models. The models in the Dectectron2 platform will be used as an alternative.

Four pre-trained models are being selected from the Detectron2 Model Zoo. The models selected are RetinaNet ResNet-50, RetinaNet ResNet-101 FPN, Faster R-CNN ResNet-50 FPN, and Faster R-CNN ResNet-101 FPN. The basic settings of the model as shown in Table VIII and Table IX, the result, and the inference images as shown in Fig. 17, Fig. 18 and Fig. 19.

TABLE VIII. BASIC SETTINGS FOR DETECTRON2 MODELS

| Settings | Options |
|---|---|
| num_classes | 2 |
| inns_per_batch (batch_size) | 2 |
| max_iter | 3600 |

TABLE IX. RESULT FOR DETECTRON2 MODELS

| Model | RetinaNet ResNet50 FPN | RetinaNet ResNet101 FPN | Faster R CNN ResNet50 FPN | Faster R CNN ResNet101 FPN |
|---|---|---|---|---|
| Average Precision (AP) @ [loU-0.50:0.95 \| area= all] | 0.23 | 0217 | 0.317 | 0.353 |
| Average Precision (AP) @ [loU-0.50:0.95 \| area= small] | -1 | -1 | -1 | -1 |
| Average Precision (AP) @ [loU-0.50:0.95 \| area= medium] | 0.050 | 0.071 | 0.167 | 0.145 |
| Average Precision (AP) @ [loU-0.50:0.95 \| area= large] | 0.263 | 0.284 | 0.388 | 0.4 |
| Average Recall (AR) @ [loU-0.50:0.95 \| area= all] | 0.261 | 0.284 | 0.422 | 0.425 |
| Average Recall (AR) @ [loU-0.50:0.95 \| area= small] | -1 | -1 | -1 | -1 |
| Average Recall (AR) @ [loU-0.50:0.95 \| area= medium] | 0.062 | 0.08 | 0.223 | 0.196 |
| Average Recall (AR) @ [loU-0.50:0.95 \| area= large] | 0.3 | 0.324 | 0.466 | 0.472 |
| Total Loss | 0.3329 | 0.2768 | 0.559 | 0.4414 |

Fig. 17. Inference image of retinaNet ResNet50 FPN.

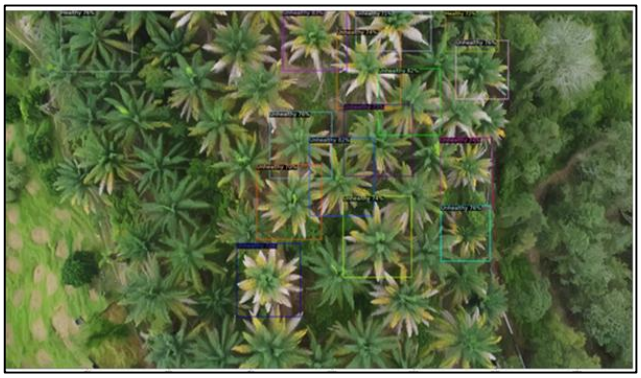

Fig. 18. Inference image of faster R-CNN ResNet50 FPN.

Fig. 19. Inference image of faster R-CNN ResNet101 FPN.

The batch size and the number of max iterations have been selected for the fine tuning process. These two parameters are essential and will significantly impact the result if the value is fine-tuned correctly. Batch size refers to the number of training images utilized in one iteration, while max_iter refers to the maximum cycle for the training process. The settings of the model as shown in Table X and Table XI, the result and the inference images as shown in Fig. 20, Fig. 21, Fig. 22, Fig. 23 and Fig. 24.

TABLE X. FINE-TUNING FOR FASTER R-CNN RESNET101 FPN

| Settings | Options |
|---|---|
| num_classes | 2 |
| ims_per_batch (batch_size) | 2/ 4 |
| max_iter | 3600/ 7200/ 9000/ 10800 |

TABLE XI. RESULT UNDER DIFFERENT SETTINGS

| Settings | Benchmark | A: 3600 iter, batch size: 4 | B: 7200 iter, batch size: 2 | C: 9000 iter, batch size: 2 | D: 10800 iter, batch size: 2 |
|---|---|---|---|---|---|
| Average Precision (AP) @ [IoU-0.50:0.95 \| area= all] | 0.353 | 0.329 | 0.342 | 0.355 | 0.333 |
| Average Precision (AP) @ [IoU-0.50:0.95 \| area= small] | -1 | -1 | -1 | -1 | -1 |
| Average Precision (AP) @ [IoU-0.50:0.95 \| area= medium] | 0.145 | 0.158 | 0.165 | 0.169 | 0.184 |
| Average Precision (AP) @ [IoU-0.50:0.95 \| area= large] | 0.4 | 0.364 | 0.382 | 0.393 | 0.362 |
| Average Recall (AR) @ [IoU-0.50:0.95 \| area= all] | 0.425 | 0.393 | 0.418 | 0.440 | 0.421 |
| Average Recall (AR) @ [IoU-0.50:0.95 \| area= small] | -1 | -1 | -1 | -1 | -1 |
| Average Recall (AR) @ [IoU-0.50:0.95 \| area= medium] | 0.196 | 0.206 | 0.212 | 0.222 | 0.259 |
| Average Recall (AR) @ [IoU-0.50:0.95 \| area= large] | 0.472 | 0.430 | 0.463 | 0.487 | 0.452 |
| Total Loss | 0.4414 | 0.3803 | 0.2853 | 0.2296 | 0.2020 |

Fig. 20. Benchmark from preliminary result.

Fig. 21. Batch size of 4 and 3600 iterations.

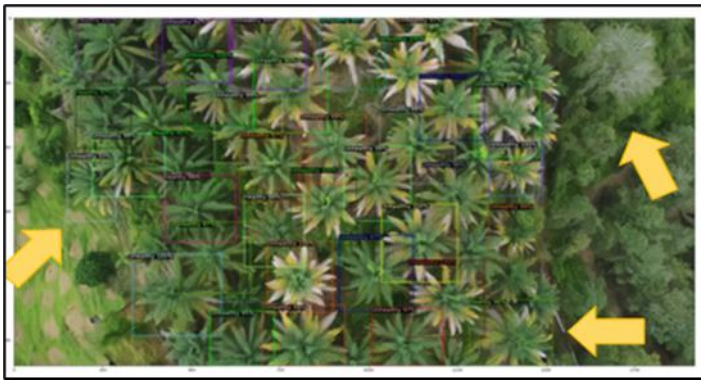

Fig. 22. Batch size of 2 and 7200 iterations.

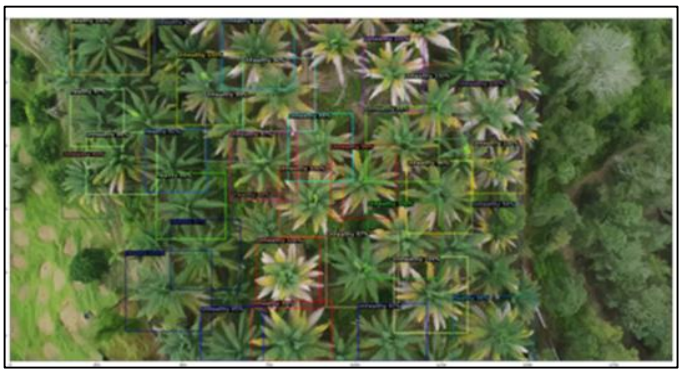

Fig. 23. Batch size of 2 and 9000 iterations.

Fig. 24. Batch size of 2 and 10800 iterations.

The fine-tuning process starts with model A by increasing the batch size to 4 while maintaining the max_iter value at 3600. These settings are made to explore the impact on model performance by increasing the batch size. The process is then continued with another three models of B, C, and D with different iterations, which are 7200, 9000, and 10800, while the batch size is kept constant at 2. The reason is to understand the effect of different numbers of max iteration on the model performance. Table X shows the performance metrics of a benchmark model from the preliminary stage and four other fine-tuned models. The model did not perform significantly better by increasing the batch size to 4. The performance metrics show that model A has a lower total loss and a slight increase in value for AP and AR in the medium area category, while the other metrics of model A dropped when compared with the benchmark model. The inference image also did not show any significant improvement in detection, as there is still a false positive detection on the top right corner of the image. Next, model B has settings of 7200 iterations and batch size of 2. The table shows that there is only a slight increase in value for AP and AR in the medium area category and a lower value of total loss (0.2853). Besides that, it did not show any significant increase in other performance metrics. However, there is an improvement in model B when comparing the inference image with the one of the benchmark model. It is shown with an arrow at the area of improvement. The false positive detection on the top right corner of the image is gone, and the undetected trees at the left side and the bottom part of the image are now detected. For model C, the max iteration is increased to 9000 iterations, and the batch size is kept constant at 2. The result shows that model C achieved the highest AP value of 0.355 for all area category, and the highest AR value of 0.44 and 0.487 for all and large area categories, respectively. Meanwhile, the total loss of model C is 0.2296, which is the second lowest among the models. The inference image of model C has no differences when compared to the one of model B. Lastly, the max iteration is set to 10800, and the batch size is kept constant at 2 for model D. Even though model D achieved the lowest value of total loss and the highest value in AP and AR for the medium area category, the value for other performance metrics dropped compared to model C of 9000 iterations. The value of AP for all and large area categories hits the lowest among all models. The inference image of model D also started to show the symptoms of overfitting as the false positive detection reappeared in the top right corner of the image. In conclusion, the Faster R-CNN ResNet101 FPN model with 9000 iterations and batch size of 4 performs the best. This experiment also shows that a two-stage detector, like the Faster R-CNN model, is better at classifying and locating the object than a one-stage detector, like RetinaNet and CenterNet. In addition, it also proved that a deeper backbone module would yield a better result.

There are some challenges throughout the project execution. The data annotation process was a challenging one. The oil palm trees are tough to label as it contains much ambiguity. Some tree crowns are yellowish because of sunlight reflection, but it does not mean the tree is unhealthy. Besides, oil palm tree crowns overlap, making it hard to determine the correct boundary for each crowns during annotation. Thus, constant communication is made with the clients on this issue so that a standardized dataset can be produced. Lastly, another challenge is the time consumption in training the TensorFlow models. The longest time to train a TensorFlow is around nine hours for the Faster R- CNN model. It is also tough to train the model as the training process disconnected from the server several times, and it will be retrained again. Thus, object detection models from alternative platforms like PyTorch and Detectron2 are being used and the training time significantly reduces to less than two hours.

## IV. CONCLUSION

As mentioned in Section III, the Faster R-CNN ResNet101 FPN model performed the best among all the models. It is then fine-tuned to achieve a better result. Batch size and max iteration are the parameters used to fine tune the model. As a result, the Faster R-CNN ResNet101 FPN model with 9000 iterations and batch size of 2 achieved the best performance compared to its

benchmark model with 3600 iterations and batch size of 2. Suggestion for future work, to explore the method of taking a picture by combine using multi modal fusion and sensor. The data might be useful by combining sensors such as lidar, hyperspectral, and SAR (Synthetic Aperture Radar) with RGB imagery to improve detection under varying the environment from different perspectives.

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# Intelligent Guitar Chord Recognition Using Spectrogram-Based Feature Extraction and AlexNet Architecture for Categorization

Dr. Nilesh B. Korade[1], Dr. Mahendra B. Salunke[2], Dr. Amol A. Bhosle[3], Dr. Sunil M. Sangve[4], Dhanashri M. Joshi[5], Gayatri G. Asalkar[6], Dr. Sujata R. Kadu[7], Dr. Jayesh M. Sarwade[8]

Assistant Professor, Department of Computer Engineering, JSPM's Rajarshi Shahu College of Engineering, Tathawade, Pune-411033, Maharashtra, India[1, 5, 6]

Assistant Professor, Department of Computer Engineering, PCET's, Pimpri Chinchwad College of Engineering and Research, Ravet, Pune-412101, Maharashtra, India[2]

Associate Professor, Department of Computer Science and Engineering, School of Computing, MIT Art, Design and Technology University, Loni Kalbhor, Pune-412201, Maharashtra, India[3]

Professor, Department of Artificial Intelligence and Data Science, Vishwakarma Institute of Technology, Bibwewadi, Pune-411037, India[4]

Assistant Professor, Department of Computer Engineering, Terna Engineering College, Mumbai, Maharashtra, India[7]

Associate Professor, Department of Information Technology, JSPM's Rajarshi Shahu College of Engineering, Tathawade, Pune-411033, Maharashtra, India[8]

***Abstract*—Chord prediction plays a key role in the advancement of musical technological innovations, such as automatic music transcription, real-time music tutoring, and intelligent composition tools. Accurate chord prediction can assist musicians, educators, and developers in constructing tools that help in learning, playing, and composing music. Background noise and audio distortions may have an impact on chord prediction accuracy, particularly in real-world situations. Chords can have distinct voicings or finger positions on the guitar, resulting in slight variations in audio representation. This study focuses on the classification of guitar chords using techniques of deep learning. There are eight major and minor guitar chords in the dataset. They have been turned into spectrograms, chromagrams, and Mel Frequency Cepstral Coefficients (MFCC) so that features can be extracted. Various deep learning architectures, including CNN, ResNet50, AlexNet, and VGG, were employed to classify the chords. Experimental results demonstrated that the spectrogram-based AlexNet model outperforms others, achieving good accuracy and robustness in chord classification. The proposed study demonstrates the efficiency of spectrograms and advanced deep learning models for audio signal processing in music applications. By automating chord detection, this study provides beneficial resources for music learners as well as educators, enabling more efficient learning and real-time feedback during practice sessions.**

***Keywords*—Chords; prediction; spectrogram; chromagram; Mel Frequency Cepstral Coefficients; AlexNet**

## I. Introduction

Nowadays people prefer to learn music online, particularly through video lessons. There is a growing demand for systems that can provide real-time feedback and support. Many aspiring musicians struggle to assess their own skill level, especially while learning to play musical instruments such as the guitar. The demand for an automated system capable of effectively identifying and classifying guitar chords is rising, as it can assist learners in determining whether they are performing the chords correctly [1].

A guitar typically contains six wires or strings stretched across the neck and body, each tuned to a distinct pitch, which makes sound when plucked or strummed [2]. The standard tuning of a guitar, from the lowest (thickest) to the highest (thinnest) string, is EADGBE. Frets are metal strips that run horizontally across the guitar neck. The frets separate the neck into parts. When you press a string against a fret, it shortens its vibrating length and changes its pitch. Theoretically, there are endless chords on a guitar due to changes in tunings, fingerings, and voicings [3]. Typically, guitarists utilize a more manageable set of chords. Based on the 12 notes of the chromatic scale, there are 12 distinct major and minor chords. Major chords, which include the root note, major third, and perfect fifth, are known for their bright, happy sound. Minor chords are typically described as having a darker, sadder sound, and they are made up of the root note, minor third, and perfect fifth [4]. The list of 12 major and 12 minor chords is presented in Table I.

TABLE I. Guitar Basic Major and Minor Chords

| Major Chords | Minor Chords |
|---|---|
| A major (A) | A minor (Am) |
| A# major (A#) or Bb major (Bb) | A# minor (A#m) or Bb minor (Bbm) |
| B major (B) | B minor (Bm) |
| C major (C) | C minor (Cm) |
| C# major (C#) or Db major (Db) | C# minor (C#m) or Db minor (Dbm) |
| D major (D) | D minor (Dm) |
| D# major (D#) or Eb major (Eb) | D# minor (D#m) or Eb minor (Ebm) |
| E major (E) | E minor (Em) |
| F major (F) | F minor (Fm) |
| F# major (F#) or Gb major (Gb) | F# minor (F#m) or Gb minor (Gbm) |
| G major (G) | G minor (Gm) |
| G# major (G#) or Ab major (Ab) | G# minor (G#m) or Ab minor (Abm) |

In our research, we demonstrate the 12 major and minor guitar chords with a standard notation system that incorporates the 6-string arrangement, fret numbers, and finger locations. This diagram is commonly used by guitarists to learn how to play each chord on the guitar. For each chord, the string number (ranging from 1 to 6, with string 1 being the thinnest and string 6 being the thickest) is specified along with the fret numbers that correspond to where the fingers should press on the fretboard [5]. For example, in the A Major (A) chord, String 6 (E) is not played, String 5 (A) is played open, String 4 (D) is pressed at the second fret with the third finger, String 3 (G) is pressed at the second fret with the second finger, String 2 (B) is pressed at the second fret with the first finger, and String 1 (E) is played open [6]. Fig. 1 presents a representation of a few chords.

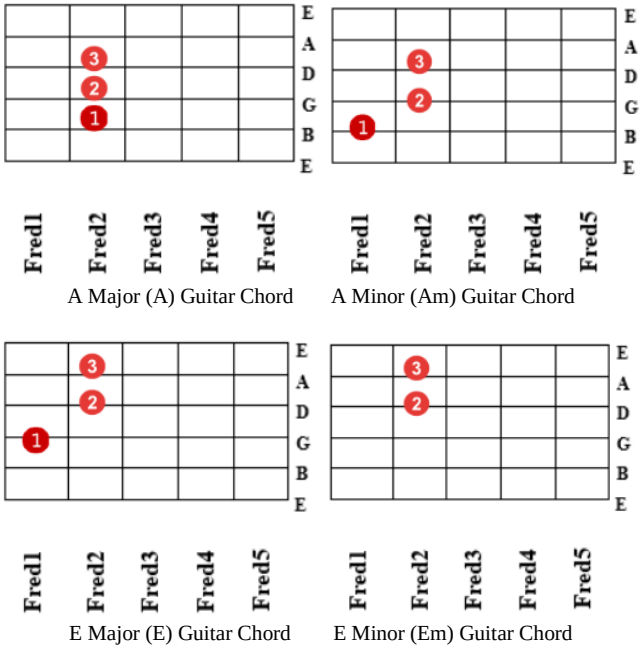



Fig. 1. Representation of chords.

To investigate the most effective representation of audio data for chord classification, we examined three extensively used feature extraction techniques: spectrogram [7], chromagram [8], and Mel-Frequency Cepstral Coefficients (MFCC) [9]. The model trained on spectrogram data outperformed the others in effectively predicting chords, demonstrating its capacity to capture pitch and harmonic relationships that are important for chord differentiation. Several deep learning architectures, such as CNN, ResNet50, AlexNet, and VGG-19, were used to perform the classification challenge [10, 11]. When trained on a limited dataset, AlexNet outperformed the other models, providing the highest accuracy while utilizing the fewest computational resources and training time. This makes AlexNet ideal for cases in which data availability is limited or rapid deployment is required. The approaches applied in the present research included preprocessing audio files to generate chromagrams, which were then scaled to standard dimensions. These representations were then utilized to train the classification models. The precision, recall, F1-score, and accuracy metrics were used to assess the performance of each architecture, ensuring an accurate assessment of its effectiveness. By evaluating the audio input from the learner's performance, it can provide immediate feedback, measure progress, and recommend areas for growth. This approach can be a useful aid for beginners studying guitar, allowing them to rapidly recognize and correct errors while practicing chords. It can function as a virtual tutor, providing assistance when a live instructor is unavailable.

The structure of this research article is outlined as follows: Section Two examines the most recent investigations on music categorization and discusses significant research gaps. Section Three illustrates the methodology, comprising details regarding the dataset, the feature extraction method, the architecture of the AlexNet model, and the assessment criteria used. Section Four discusses the performance of various feature extraction techniques and models in predicting chords based on the selected metrics. Finally, Section Five presents the conclusion, followed by a list of references used.

## II. Literature Survey

Automated chord recognition is an essential aspect of music information retrieval (MIR) that assists with applications such as music transcription, evaluation, and production. The work describes a chord detection method that combines a revised Pitch Class Profile (PCP) feature with Support Vector Machines (SVM) for classification. The PCP feature enhances music chord recognition by efficiently capturing harmonic structures while reducing noise and octave-related ambiguity. SVM is employed as it has high categorization proficiency, allowing precise chord detection across varied musical works. The methodology was evaluated on four songs: *Good to Be Alive*, *Ghost*, *The Royal Wedding Song*, and *Trouble I'm In*, with accuracy rates of 91%, 93%, 95%, and 98%, respectively. Investigations reveal that the approach performs well at detecting chord progressions, with satisfactory outcomes. Employing PCP as a classifier allows for evaluating a song's emotional undertones quickly and accurately, with broader ramifications. It enhances the comprehension of musical concepts by providing essential insights into theoretical frameworks [12].

The traditional methods for characterizing audio signals use handmade features such as MFCC, spectral centroid, or zero-crossing rate (ZCR). The recent improvements have centered on DL approaches and intelligent feature extraction to boost performance. The investigation explores the implementation of textural features and Mel-spectrograms produced from the short-time Fourier transform to capture the frequency content of an audio signal for accurate music identification. Texture features, primarily utilized in processing images, produced promising results in audio analysis by capturing patterns and fluctuations in representations of spectrograms. A diversified song recording dataset of 404 audio files from four unique classes of Arabic music has been gathered and transformed into Mel-spectrograms, using which various texture features are extracted. Each Mel-spectrogram undergoes a two-dimensional Haar wavelet processing before feature extraction with Local Binary Patterns (LBP), Histogram of Oriented Gradient (HOG), and Gray Level Co-occurrence Matrix (GLCM). To assess classification performance, several machine learning methods were used, and the proposed approach was evaluated on two datasets: the recently collected Arabic music dataset and the commonly utilized GTZAN dataset. Using five-fold cross-

validation, the research findings demonstrated that the XGB classifier performed better, giving 97.8% accuracy, 97.7% F1- score, 97.7% recall, and 97.8% precision [13].

Folorunso et al. explore the understudied topic of automatic genre categorization for Nigerian traditional music utilizing the ORIN dataset, which comprises 478 music with five genres: Apala, Fuji, Waka, Juju, and Highlife. The Librosa Python package has been utilized to retrieve timbral texture and tempo information for 30-second portions of each song. The study employed the global mean (Tree SHAP) method to assess feature significance and its impact on the model for classification. Timbral features of texture allow for differentiation between comparable beats and melodies. The timbral texture can be used to compute a variety of properties such as MFCC, spectral centroid, tempo, flatness, bandwidth, contrast, sample-silence, zero-crossing-rate, and so on. After the extraction, information about the level of variance and dispersion is extracted, including mean, skewness, kurtosis, standard deviation, minimum, and maximum values. The methodology, which combines feature extraction with classifiers, delivers insights into the performance of several models for genre categorization. The Tree SHAP method is based on Shapley Additive Explanations (SHAP), a game-theoretic strategy for assigning importance scores to input data in interpreting tree-based model predictions. Four classifiers were implemented for genre classification, and among these, the XGBoost classifier has an outstanding accuracy of 81.9% and recall of 84.5% [14].

Categorizing music genres can be automated, and many approaches have been presented in recent years for accomplishing this objective; however, analysis shows that there is still an inequality between the observed outcomes and an optimal categorization approach. The Teng Li presented an approach that involves preprocessing the input signals and then demonstrating the properties of each signal using a combination of MFCC and STFT features. The proposed technique combines two independent CNN models optimized with black hole optimization (BHO) to evaluate MFCC and STFT data, and the results of the two models are integrated to identify the music genre by applying a SoftMax classifier. The GTZAN and Extended-Ballroom datasets were used for assessing the performance of the suggested technique for categorizing music genres. Test outcomes revealed that the suggested approach obtained a classification accuracy of 95.2% on GTZAN and 95.7% on Extended-Ballroom datasets [15].

Carsault et al. investigate the real-time evaluation and forecasting of musical chord patterns to improve innovative methods in composing music and performance. The chords have inherent hierarchical and functional linkages that are critical for comprehending and anticipating musical forms. The input is an audio real-time recording of a musician, which is processed in order to produce a time-frequency representation assisting in the identification of chord sequences. Each beat of the music is then tagged with a chord, and the prediction module makes use of these chords in recommending what might occur next in the sequence. Chord prediction employs several loss functions, such as Tonnetz and correct notes, for boosting accuracy in both diatonic and non-diatonic music. The Bi-LSTM model is utilized in chord prediction because it retains past and future interdependence in chord sequences, making it ideal for sequential music prediction services. This method provides a deeper understanding of the model's performance than typical accuracy measurements [16].

Deep learning models substituted earlier ML approaches that relied on hand-crafted features and transformed the area of music classification by allowing pattern features to be learned automatically. Researcher Jiyang Chen stated that CNNs face challenges in accurately simulating global features that are essential for identifying music signals with temporal properties due to the influence of the local receptive field. The proposed hybrid architecture based on CNN and Transformer encoder worked on transforming audio signals into mel spectrograms. The CNN architecture consists of four 2D convolutional layers, followed by batch normalization, max pooling, and ReLU as the activation function. The transformer encoder has two layers, each of which has multi-head attention, a multi-layer perceptron, and two normalizing layers. The CNN primarily captures low- level and localized features from the spectrogram, followed by the transformer encoder, which processes these features globally to extract high-level and abstract semantic information. The approach is evaluated on the GTZAN with 100,000 tracks and FMA datasets, contains 8000 music clips, and produces amazing outcomes with lower parameters and an increased inference speed, with accuracy 87.41, precision 87.93, recall 87.58, and F1 score 87.28 [17].

As music is a sort of time-series data, which makes it difficult to build a robust MGC, Zhiqiang Zheng introduced the DL-Enabled MGC approach, which aims at boosting the precision and effectiveness of genre categorization work. The proposed strategy extracts significant features from raw musical data by converting pitches from input Musical Instrument Digital Interface (MIDI) files into vector sequences employing the Pitch2vec method. A hybrid model employs bidirectional long short-term memory optimized using cat swarm optimization to successfully capture temporal dependencies in music data. CSO is a swarm intelligence-based optimization technique that fine-tunes hyperparameters, including learning rate, number of hidden layers, and activation functions, resulting in improved model convergence. BiLSTM analyzes data both forward and reversed, facilitating the model to capture past and future dependencies concurrently. The DLE-MGC technique was examined using the MIDI music dataset containing thirteen types of music utilizing 1000 and 2000 epochs. The results demonstrate that with 1000 epochs, the DLE-MGC methodology has offered a precision, recall, F1-score, and accuracy of 94.97%, 95.97%, 96.53%, and 95.42%, and with 2000 epochs, 95.84%, 95.93%, 96.71%, and 95.77%, respectively [18].

Yu-Huei Cheng presents an experimental approach for recognizing genres of music that employs graphical representations of sound data and effective ML algorithms. To achieve excellent classification accuracy, the visual Mel spectrum was employed as a feature representation, together with the YOLOv4 neural network architecture. The visual Mel spectrum, which captures both temporal and spectral aspects of the music, is provided as input for the classification model, allowing for the extraction of rich, discriminative properties relevant to several music genres. The YOLOv4 architecture has

been chosen as its potential to effectively handle visual data makes it suitable for interpreting visual Mel spectrograms, resulting in effective feature learning and categorization. The 1.6 GB GTZAN dataset was used for the assessments, and the proposed technique achieved 91.49% accuracy for training and 97.93% for testing. This study uses YOLO, which has never been utilized for music genre classification, and it has research significance [19].

A review of previous studies indicates that the majority of music analysis research focuses on genre classification rather than chord prediction. There is a significant gap in research on automatic chord recognition. The majority of studies use CNN for music classification tasks like genre and instrument recognition. While deep learning models are commonly used for classification, the effect of various feature extraction methodologies (such as chromagram, spectrogram, and MFCC) on model performance has not been thoroughly investigated. Most research does not examine how different feature representations impact classification accuracy, leaving a gap in determining the optimal characteristics for chord recognition.

## III. Methodology

We loaded the chords dataset containing .wav audio files for different chord categories and extracted the Chromagram, spectrogram, and MFCC features. The normalization is performed on each extracted feature to ensure that all features are on the same scale [20]. Each feature set was used to train and evaluate several deep learning models in order to determine the most effective feature extraction technique and chord prediction model. PyAudio was used to capture live audio from the guitarist while he performed in order to figure out chords in real time. The selected deep learning model was then used to determine the correct chord [21-23]. The proposed methodology is described in Fig. 2.

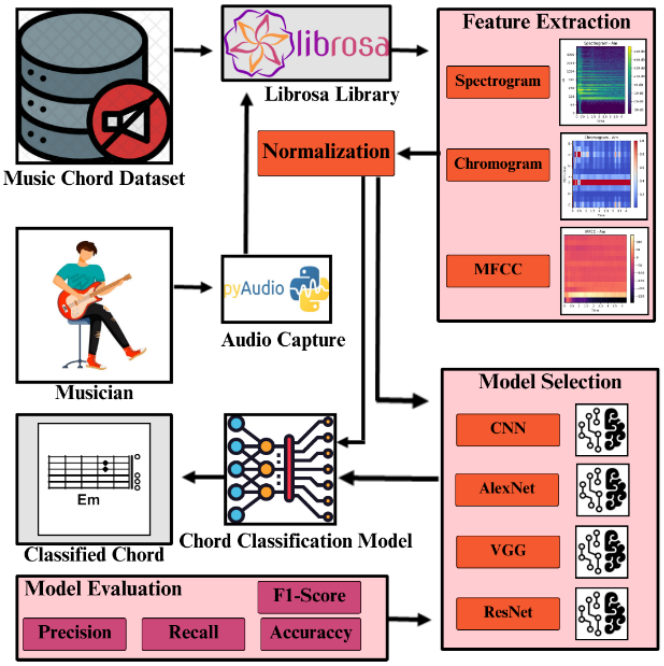



Fig. 2. Proposed methodology.

### A. Dataset

We collected a dataset of 1440 audio files in .wav format, each representing eight distinct guitar chords: [Minor: {Em', 'Dm', 'Am', 'Bdim'}, Major: {G', 'C', 'Bb', 'F'}]. Each chord was played on a guitar by hand, with speed and duration variations to imitate several acoustic aspects associated with performances in real time. This variation in playing approach promises that the dataset covers a wide range of musical expressions, which enhances the robustness of the chord prediction model. The dataset establishes a robust foundation for constructing and evaluating deep learning models for real-time chord recognition in music. The 1,152 .wav files, representing 80% of the chord dataset, were employed to train the chord prediction model, while the remaining 288 files, which is 20%, were used to test its accuracy and effectiveness.

### B. Feature Extraction

Feature extraction is a critical step in chord prediction because it transforms raw audio data into meaningful representations that can be used by machine learning algorithms. We employed three fundamental feature extraction strategies: chromagram, spectrogram, and MFCC, each of which captured a different aspect of the audio stream. Fig. 3 demonstrates the representation of the chromatogram, spectrogram, and MFCC for chords Am and C.

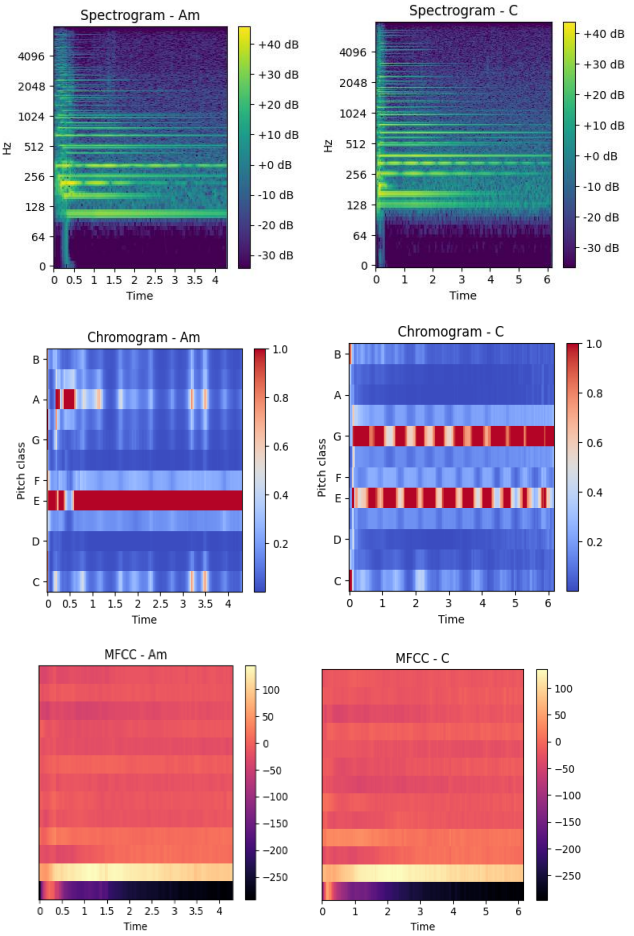



Fig. 3. Representation of chromagram, spectrogram, and MFCC for chord Am & C.

*1) Spectrogram*: Spectrograms are extensively utilized in domains such as machine learning, voice analysis, audio processing, and seismology, particularly in applications like environmental sound classification and recognition of speech. A spectrogram is a two-dimensional graph where a third dimension is represented by color. Time is represented by the horizontal X-axis, which moves from left to right, while frequency is represented by the vertical Y-axis, which goes from low at the bottom to high at the top [24]. A frequency's amplitude or loudness at a given moment is indicated by its color intensity; brighter colors imply higher, louder amplitudes, while darker shades suggest lower amplitudes. A signal is usually broken down into its frequency components over short time intervals using the Short-Time Fourier Transform (STFT) expressed in Eq. (1), which serves as a foundation for building spectrograms [25]. Eq. (2) uses the squared magnitude of the STFT to derive the spectrogram.

$$S(t,f) = \int_{-\infty}^{\infty} x(\tau)\omega(\tau - t)e^{-j2\pi f\tau}\, d\tau \quad (1)$$

$$Spectrogram(t,f) = |S(t,f)|^2 \quad (2)$$

The sliding window current time location represented by t and f represents the frequency being analyzed. The input signal as a function of time is represented by x(τ). A window function w(τ−t) centered at time t isolates a segment of the signal to analyze. The Fourier kernel $e^{-j2\pi f\tau}$ that transforms the signal into the frequency domain.

*2) Chromagram*: A chromagram is a representation in the form of an image of the intensity or energy of the pitch classes or musical notes in a signal, irrespective of their octave. As it can capture the melodic and harmonic elements of audio signals, it is frequently utilized in music information retrieval (MIR). The vertical Y-axis represents musical notes that are classified into twelve pitch classes (e.g., C, C#, D, ..., B) in the Western music system, and the horizontal X-axis represents the time evolution of the signal [26]. The color or brightness of a cell in the chromagram represents the energy or intensity of a specific pitch class at a given time. The audio signal x(n) (where n represents discrete time samples) is transformed into the frequency domain using the STFT using Eq. (1). The Eq. (3) translates frequencies in the spectrum to one of the twelve pitch classes [27].

$$p = mod\left(\left\lfloor 12.log_2\left(\frac{f}{f_{ref}}\right)\right\rfloor, 12\right) \quad (3)$$

where, p is Pitch class ranges from 0 to 11, corresponding to C, C#, ..., B. The f represents frequency in Hz, and $f_{ref}$ refers to reference frequency, typically 440 Hz. The $\lfloor\cdot\rfloor$ symbol represents the floor function, which truncates to the largest integer less than or equal to the value. For each pitch class p, the total energy over all octaves at time t is calculated. The chromagram C(t,p) can be calculated as follows:

$$\mathrm{C(t,p)} = \sum_{f\in F(P)}|X(t,f)| \quad (4)$$

where, |X(t,f)| represents the magnitude of the STFT at time t and frequency f. The set F(p) contains all frequencies f that correspond to the pitch class p. To achieve uniform representation across time frames, normalization is employed, expressed in Eq. (5) [28].

$$NC(t,p) = \frac{C(t,p)}{max_p C(t,p)} \quad (5)$$

where, *NC(t,p)* is the normalized chromagram, and maximum chromagram intensity over all pitch classes for a particular time frame t is represented by $max_pC(t,p)$.

*3) Mel-frequency cepstral coefficients (MFCC)*: MFCCs are created by translating an audio signal into a set of coefficients that represent the signal's short-term power spectrum on the Mel frequency scale, which is commonly utilized in speech and audio signal processing operations [28]. MFCCs give a concise representation of an audio signal's spectrum features and have been designed to represent the human auditory system's perception of sound. To amplify high frequencies and balance the spectrum, pre-emphasis is applied to the signal, assisting to retain key information for analysis.

$$Y[n] = X[n] - \alpha \cdot X[n-1] \quad (6)$$

where, X[n] represents the original signal, Y[n] represents the pre-emphasized signal, and α is the coefficient for pre-emphasis, usually 0.95. To examine short-term features, the signal is separated into small overlapping frames spanning about 20-40 milliseconds. Each frame represents a quasi-stationary segment of the signal. To eliminate edge effects, a window function w[n] (especially Hamming) gets applied to each frame 1 to N expressed in Eq. (7) [29].

$$w[n] = 0.54 - 0.46 \cdot cos\left(\frac{2\pi n}{N-1}\right) \quad (7)$$

The number 0.54 ensures that the window has a "base value" at its center, while -0.46 multiplied by the cosine function modifies the form of the window, regulating how quickly the window tapers to zero at its edges. The power spectrum is obtained using the Fourier transform, which transforms the windowed frame into the frequency domain.

$$X[k] = \sum_{n=0}^{N-1} x[n] \,.\, e^{-j2\pi kn/N} \quad (8)$$

where, X[k] is frequency components and k represents the frequency bin index. To map the power spectrum to the Mel scale m(f), it first passes through a Mel filter bank (MFB) expressed in Eq. (9). The scaling ratio 2595 was used to translate frequencies from the Hertz scale to the Mel scale, and the constant 700 is a reference frequency at which the Mel scale begins to diverge significantly from linear scaling. Triangular filters concentrate distinct frequency bands to replicate human hearing. The energy S[m] for each Mel filter is calculated using Eq. (10), where Weight of the $k^{th}$ frequency in the $m^{th}$ filter. Logarithmic scaling L[m] is used to simulate the human auditory system's perception of sound expressed in Eq. (11) [30].

$$m(f) = 2595.log_{10}\left(1 + \frac{f}{700}\right) \quad (9)$$

$$S[m] = \sum_k |X[k]|^2 . H_m[k] \quad (10)$$

$$L[m] = log(S[m]) \quad (11)$$

The Discrete Cosine Transform (DCT) is used to decorrelate log Mel energy and compress them into MFCC coefficients

using Eq. (12), where M is number of Mel filters and n is the coefficient index.

$$MFCC[n] = \sum_{m=0}^{M-1} L[m] \cdot cos\left(\frac{\pi n(2m+1)}{2M}\right) \quad (12)$$

The overall process for MFCC computation C(t, n) is represented in Eq. (13), where t is the time frame index and n is the MFCC coefficient index.

$$C(t,n) = DCT\left(log\left(MFB\left(FFT(x(t))\right)\right)\right) \quad (13)$$

### C. Model Selection

Several deep learning architectures were employed to evaluate the chord prediction performance, including CNN, AlexNet, VGG-19, and ResNet-50. The best models were picked based on their demonstrated effectiveness in audio categorization tasks utilizing assessment measures. CNN is a fundamental deep learning model that can extract hierarchical features from input data while accurately capturing spatial patterns, making it suitable for a wide range of classification applications [31]. AlexNet is a deep CNN architecture designed for rapid feature extraction and classification. It employs stacked convolutional layers, ReLU activation, and dropout to improve generalization. A VGG-19 is a deeper convolutional network with 19 layers known for its identical design and potential to capture intricate patterns with small receptive fields and dense layers. ResNet-50 is a residual learning framework that uses skip connections to address the problem of vanishing gradient, resulting in deeper network training and improved classification accuracy [32].

*1) AlexNet*: AlexNet is a foundational baseline in deep learning for image classification. AlexNet consists of five convolutional layers for feature extraction and three fully connected layers for classification. AlexNet additionally uses max-pooling for spatial dimensionality reduction and GPUs for parallel processing, allowing for effective training on big datasets. It employs ReLU activation functions to incorporate nonlinearity, dropout to reduce overfitting, and data augmentation to improve generalization [33]. The acceptable input image shape is 224×224×3. The first convolution layer extracts low-level characteristics such as edges and corners using 96 filters of size 11×11 with a stride of 4 and an output of 55×55×96. The second convolution layer captures more detailed features and applies local response normalization (LRN). It uses 256 filters of size 5×5×96 with a stride of 1 and generates an output of 27×27×256. Fig. 4 presents an in-depth description of the AlexNet architecture layers, including filter size, filter number, stride, input and output sizes [34].

### D. Model Evaluation

*1)* Various metrics for assessment, such as accuracy, precision, recall, and F1-score, were employed for evaluating the feature extraction technique and model's performance in music chord prediction. These metrics provide an extensive assessment of the model's potential to accurately categorize chords while balancing false positives and false negatives [35-37]. The TP represents the instances where the model correctly predicts the positive class, and TN are the Instances where the model accurately identifies the negative class. The FP is the number of instances for which the model incorrectly classifies it as positive, and the FN is the number of instances for which the model incorrectly classifies it as negative.

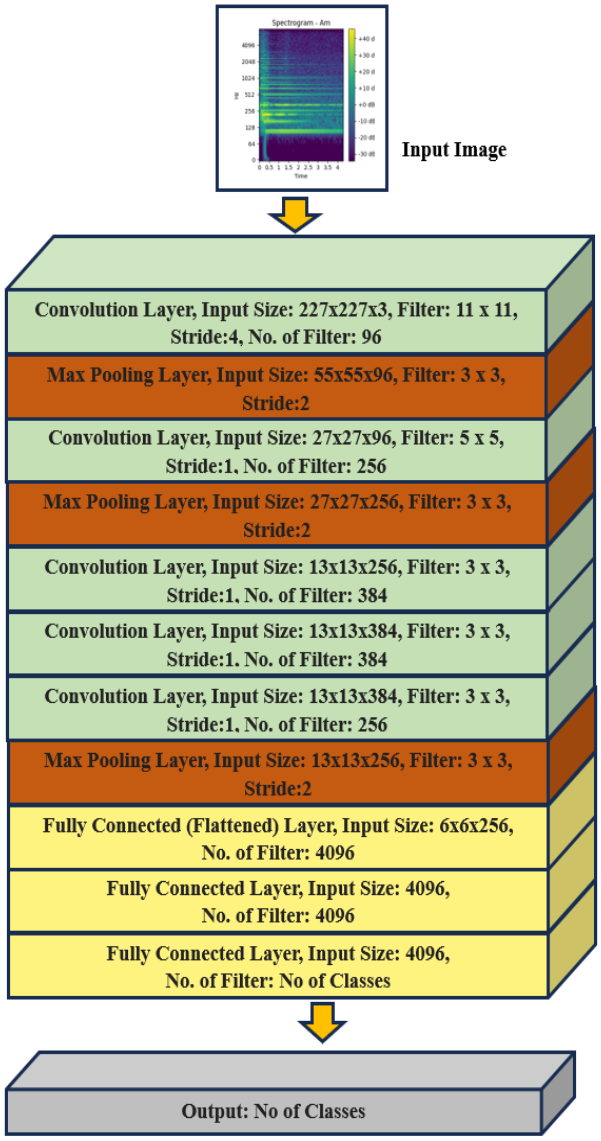



Fig. 4. AlexNet architecture.

$$\text{Accuracy} = \frac{Sum\ of\ Accurately\ Forecasted\ +ve\ samples\ [TP]\ and\ -ve\ Samples\ [TN]}{Total\ Samples(N)} \quad (14)$$

$$\text{Precision} = \frac{Accuately\ forecasted\ +ve\ samples\ [TP]}{sum\ of\ Accuatly\ forecasted\ +ve\ samples\ [TP]\ and\ incorrect\ forecasting\ as\ +ve\ [FP]} \quad (15)$$

$$\text{Recall} = \frac{Accuatly\ forecasted\ +ve\ samples\ [TP]}{Sum\ of\ Accuatly\ forecasted\ +ve\ samples [TP]\ and\ incorrect\ forecasting\ as\ -ve\ [FN]} \quad (16)$$

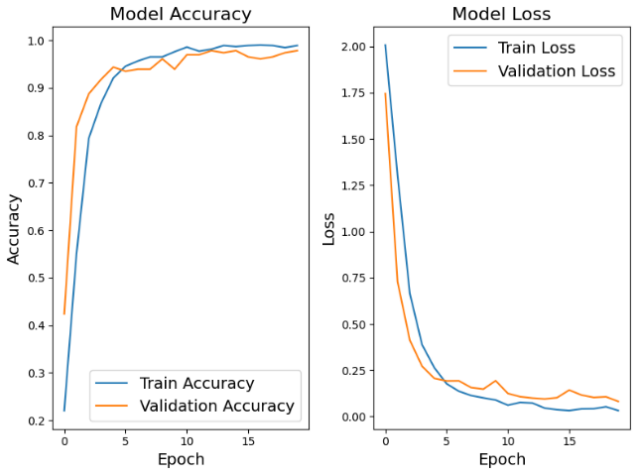
$$\text{F1Score} = 2 * \frac{[\text{Precision} * \text{Recall}]}{[\text{Precision} + \text{Recall}]} \quad (17)$$

## IV. Result and Discussion

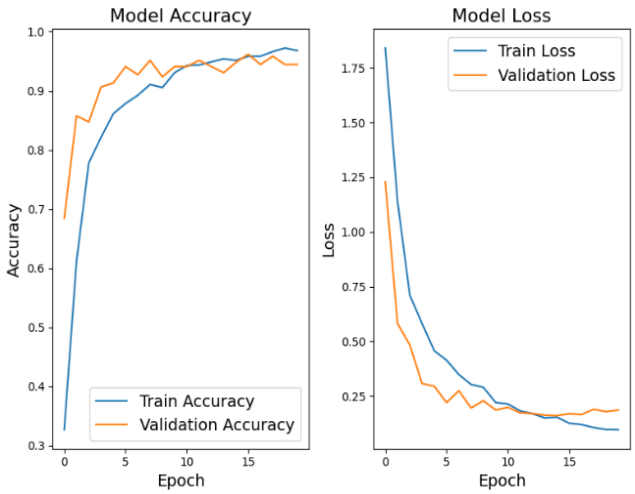
The research study has been carried out on Google Colab, using a T4 GPU for accelerated training. The chords dataset is stored on Google Drive and mounted with the Colab notebook for simple retrieval. Librosa is used for feature extraction, and Keras is utilized to build the CNN model and its variants.

### A. Evaluation of Spectrogram, Chromagram, and MFCC Features

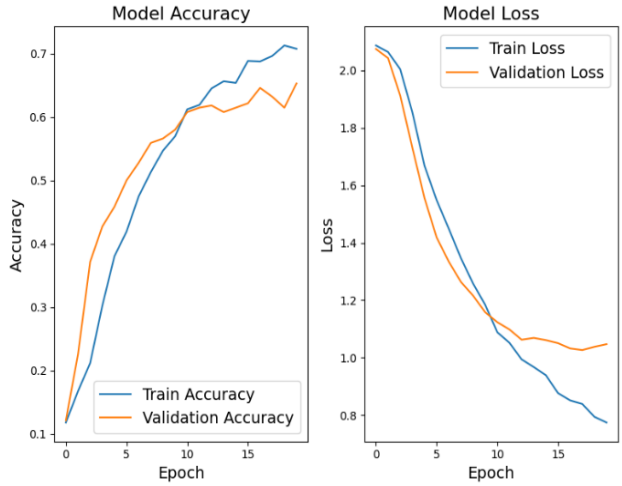
The dataset contains 1440 .wav audio files representing eight different major and minor chords, split into training and testing sets in an 80:20 ratio. To assess the effectiveness of feature extraction approaches, a CNN is trained on each method employing a similar training set. The effectiveness of CNN models trained using different feature extraction techniques was evaluated by plotting training & validation accuracy and loss against the number of epochs. Fig. 5 demonstrates the performance of each feature extraction strategy during CNN training.




Spectrogram




Chromagram




MFCC

Fig. 5. Performance of CNN model trained on spectogram, chromagram and MFCC.

CNN trained on MFCC features has less satisfactory accuracy (65%) than spectrogram and chromagram models. The loss reduction is not as smooth, demonstrating that the model has difficulty with feature representation. The model does not fully converge within 20 epochs, indicating the need for additional training or hyperparameter adjustment. CNN models based on spectrograms and chromagrams outperform MFCC-based CNN models. The spectrogram-based CNN is more accurate, converges in fewer epochs, and has closely aligned training and validation accuracy and loss values, indicating stable learning. In comparison, the chromagram-based CNN takes considerably more epochs to converge, achieves slightly reduced accuracy compared to the spectrogram-based model, and has a greater gap between training and validation accuracy and loss values. The performance of each feature extraction strategy for the test. WAV sound files are presented in Table II.

TABLE II. Performance of CNN on Different Feature Extraction Techniques

| Model | Feature Extraction Techniques | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| CNN | Spectrogram | 0.94 | 0.95 | 0.94 | 0.94 |
| | Chromagram | 0.93 | 0.94 | 0.93 | 0.93 |
| | MFCC | 0.65 | 0.67 | 0.65 | 0.65 |

The results demonstrate that the spectrogram-based CNN model delivers the highest accuracy of 94%, with other assessment measures at 0.94 each. This shows that spectrograms efficiently capture the time-frequency representation of audio inputs, resulting in reliable feature extraction for chord categorization. The chromagram-based CNN model likewise revealed strong performance, with an accuracy of 93%. However slightly less accurate than the spectrogram-based model, the chromagram technique accurately represents harmonic content, offering it as an acceptable alternative for chord detection tasks. MFCCs primarily capture spectral envelope information and are frequently employed in speech processing; however, due to their limited ability to represent harmonic structures, it may be inefficient for musical chord classification.

### B. Evaluation of Spectrogram Based Deep Learning Architecture

Choosing an appropriate architecture capable of effectively capturing the extracted feature for accurate chord detection is a vital component of the chord prediction problem. In this experiment, we trained CNNs and their variants, such as AlexNet, VGG-19, and ResNet-50, on spectrogram-based features and evaluated their performance using standard metrics. Table III summarizes the performance of each spectrogram-based model.

TABLE III. PERFORMANCE OF SEVERAL CNN VARIANTS ON SPECTOGRAM

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| CNN [38-40] | 0.94 | 0.95 | 0.94 | 0.94 |
| AlexNet | 0.96 | 0.97 | 0.97 | 0.97 |
| VGG-19 | 0.77 | 0.80 | 0.77 | 0.77 |
| ResNet-50 | 0.91 | 0.92 | 0.91 | 0.91 |

AlexNet consistently outperformed the other models examined, revealing its potential to capture pertinent information in the spectrogram and being well-suited for the chord prediction task, offering a balanced performance in both detecting and properly classifying guitar chords. The result shows that ResNet-50 and VGG-19 are deeper architectures having more parameters. These deeper models are more suitable for larger datasets, where they may learn from a diverse set of features. With a limited dataset of 1440 samples, these architectures may struggle to generalize successfully, resulting in overfitting. On the other hand, AlexNet and CNNs are less likely to overfit due to their more compact structure, and they can extract useful information from a smaller dataset without becoming overly specialized in it. Fig. 6 demonstrates the performance of AlexNet trained on spectrograms. The confusion matrix demonstrates in Fig. 7 the performance of AlexNet on the testing dataset.

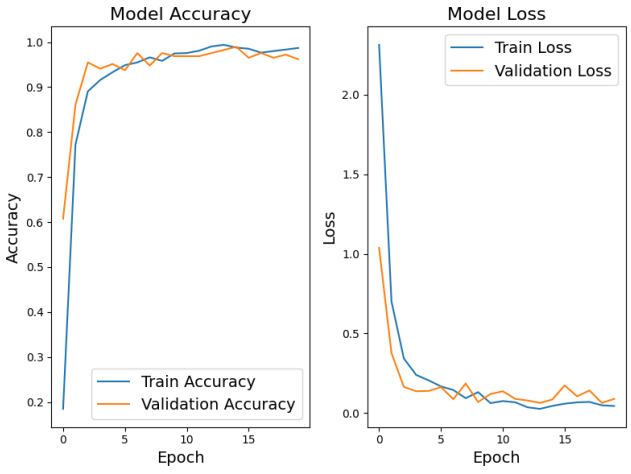



Fig. 6. Performance of AlexNet model trained on spectogram.

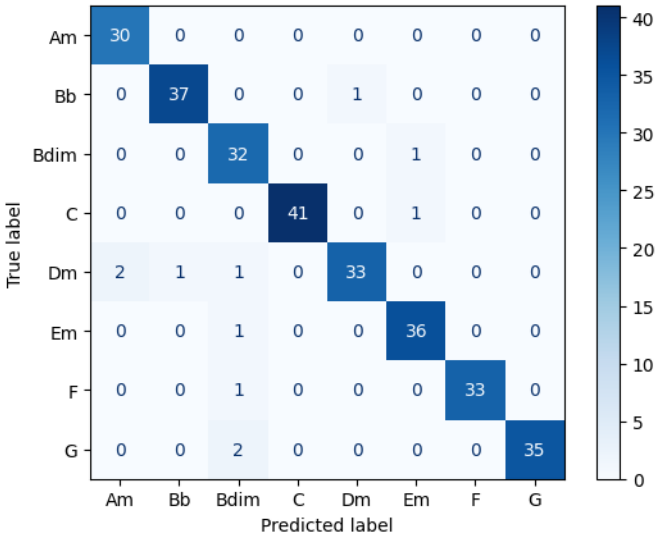



Fig. 7. Confusion matrix of AlexNet model trained on spectogram.

## V. CONCLUSION

Intelligent guitar chord categorization is a significant advancement towards improved music transcription processes, assisting musicians and growing music learning tools. Implementing deep learning approaches can build a robust system that appropriately recognizes chords from audio signals, eliminating the need for manual intervention and strengthening real-time chord recognition. The experimental results reveal that spectrogram-based models provide the best classification performance, accurately discriminating distinct chords as compared to chromagram and MFCC-based approaches. AlexNet performed outstandingly on a smaller dataset with minimal training time, making it suitable for low-data scenarios in comparison with CNN, VGG-19, and ResNet-50 architectures. The investigated training and validation accuracy/loss curves, confusion matrices, and key classification metrics demonstrate that spectrogram-based AlexNet architectures outperform other architectures trained on several feature extraction methods for chord categorization. Future studies might concentrate on expanding the dataset to foster model generalization and incorporating transformer-based designs for better feature extraction. Furthermore, incorporating the trained model with real-time applications for live chord detection and music analysis can increase its practical applicability. Future research will also concentrate on further enhancing computing efficiency in mobile and embedded devices.

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# Portable and Lightweight Signal Processing Approach for sEMG-Based Human–Machine Interaction in Robotic Hands

Ngoc-Khoat Nguyen
Faculty of Control and Automation, Electric Power University, Hanoi, Vietnam

***Abstract*—Surface electromyography (sEMG) presents a viable biosignal for the control of robotic prosthetic hands, as it directly correlates with underlying muscle activity. This study introduces an efficient, computationally lightweight signal processing methodology designed for real-time embedded systems. The proposed methodology comprises a preprocessing pipeline, incorporating bandpass and notch filtering, followed by segmentation via overlapping sliding windows. Time-domain features, specifically Mean Absolute Value (MAV), Zero Crossing (ZC), Waveform Length (WL), Slope Sign Change (SSC), and Variance (VAR), are extracted to characterize relevant muscular activation patterns. By prioritizing computational efficiency and embedded system feasibility, this method establishes a practical framework for user intent recognition and real-time control of wearable robotic hands, particularly within assistive and rehabilitative applications. The experimental findings clearly indicate that the extracted features effectively differentiate between various hand gestures, allowing for accurate, real-time control of the wearable robotic hand. The system's high responsiveness, low latency, and resilience to noise underscore its suitability for assistive and rehabilitative applications. With its focus on computational simplicity and feasibility for embedded implementation, the proposed method provides a practical basis for recognizing user intent in human-machine interaction systems.**

***Keywords*—sEMG; myo-prosthesis; myosignals; human–prosthesis interface; signal processing**

## I. Introduction

The upper limb plays a crucial role to a wide spectrum of daily human activities, encompassing both intricate manipulations, such as object grasping and writing, and complex movements requiring multi-joint coordination [1]. Anatomically, the upper limb comprises distinct segments-the hand, forearm, and upper arm-functioning through the coordinated interaction of the central nervous system, musculoskeletal system, and environmental sensory feedback. This inherent complexity presents substantial challenges in the design of artificial prosthetic systems, particularly robotic hands, where dexterity, precision, and user-intent-driven control are paramount. The partial or complete loss of an upper limb, resulting from trauma, disease, or other etiologies, can significantly impair an individual's quality of life, self-care capabilities, and social integration.

In recent years, a growing number of studies have explored the use of bio-signals originating from the human body to control prosthetic limbs, due to their rich information content regarding motor intentions. Among these, electromyography (EMG) signals have been extensively investigated for their ability to reflect muscle activity [2]-[4]. However, raw surface EMG (sEMG) signals cannot be directly used for motion recognition or robotic control due to their inherent spatial and temporal complexity [5]. Factors such as electrode displacement, muscle fatigue, variability in contraction intensity, and inter-subject differences contribute to reduced accuracy and repeatability in EMG-based control systems [6], [7].

Various techniques have been employed to process EMG signals, yet the core processing pipeline remains largely consistent. Initially, EMG signals are amplified and filtered after acquisition. This is particularly crucial in clinical or rehabilitation scenarios where residual muscle strength may be weak, resulting in significantly lower sEMG amplitudes compared to those in healthy individuals. Proper filter and amplifier design not only improves the signal-to-noise ratio (SNR) but also enhances the reliability of extracting relevant motor information from the signal [8].

Following preprocessing, sEMG signals are segmented using time windows, dividing the continuous data into short, fixed-length segments. Overlapping windowing is the most commonly adopted method, with the choice of window size and stride length being critical for balancing latency and accuracy. Each segment is then used to extract features that characterize muscle activity over the corresponding time interval [9].

Extracted features can belong to the time domain (TD), frequency domain (FD), or time–frequency domain (TFD). Time-domain features are directly calculated from raw sEMG signals and are functions of time [10]. TD features are widely favored due to their simplicity and computational efficiency, making them well-suited for real-time control systems. Common TD features include Mean Absolute Value (MAV), Zero Crossings (ZC), Waveform Length (WL), Slope Sign Changes (SSC), and Variance (VAR), which reflect the intensity, shape, and variation of the EMG signal. These features serves as useful inputs for subsequent classification or control stages, and have been extensively studied for EMG recognition tasks [11]–[13]. For instance, in [11], six TD features (MAV, WL, RMS, AR, ZC, SSC) were used to classify seven hand gestures, with Support Vector Machines (SVM) achieving the highest accuracy (95.26 per cent) compared to LDA (92.58 per cent) and k-NN (86.41 per cent).

In addition to TD features, FD features also play a key role in describing the spectral properties of EMG signals [14]. By

applying spectral analysis techniques such as the Fast Fourier Transform (FFT), indicators such as spectral energy, Mean Frequency (MNF), and Median Frequency (MDF) can be extracted. FD features are commonly used in fatigue analysis or combined with TD features to improve classification performance [13]. Time–frequency domain transformations such as the Short-Time Fourier Transform (STFT), FFT, and wavelet transforms preserve both TD and FD characteristics of the signal. However, TFD-based methods remain relatively underexplored due to their complexity and limited interpretability [8].

After extracting EMG features from one or more domains, the next step is to classify or recognize the user's intended movements. This is a crucial stage that translates physiological signals into control commands for robotic hands. Numerous machine learning algorithms have been successfully employed for EMG classification, ranging from traditional methods such as k-Nearest Neighbors (k-NN) [15], Linear Discriminant Analysis (LDA) [16], [23], and Support Vector Machines (SVM) [11], [17]–[19], to advanced deep learning models such as Convolutional Neural Networks (CNN) [20], [21] and Recurrent Neural Networks (RNN) [22]. Simpler models like LDA and SVM are often preferred in real-time systems due to their low computational overhead and effectiveness with linearly or near-linearly separable features. On the other hand, deep learning models can directly learn representations from raw or time–frequency-transformed data such as spectrograms or scalograms, yielding higher accuracy at the cost of increased computational requirements.

This study focuses on the preprocessing and feature extraction stages of sEMG signals as a foundation for recognizing user intent in robotic hand control. The signal undergoes preprocessing steps, including high-pass filtering, notch filtering, and low-pass filtering, to reduce noise and normalize data. Subsequently, time-domain features such as MAV, ZC, WL, SSC, and VAR are extracted using a sliding window technique, providing the necessary inputs for later classification and control stages.

The main contribution of this paper is the proposal and evaluation of a simple yet effective sEMG signal processing method that can be integrated into real-time embedded systems such as microcontrollers or wearable robotic control devices. This research lays the groundwork for incorporating machine learning techniques that enable more intuitive and adaptive robotic control. Additionally, it contributes to the development of user-intent-based control systems for robotic hands, targeting applications in rehabilitation and assistive technologies.

The subsequent sections are organized as follows: Section II covers the materials and methods used for sEMG signal acquisition and processing, detailing the signal conditioning and feature extraction steps. Section III explains the integration of the proposed method for real-time robotic hand control and describes the validation experiments performed across diverse hand gestures. Section IV presents a discussion centered on the results of these experiments, including an analysis of the proposed method's benefits and drawbacks. Lastly, Section V summarizes the key findings and identifies potential avenues for future work.

## II. Materials and Methods

### A. Signal Analysis

*1) sEMG acquisition hardware*: In this study, the surface electromyography (sEMG) sensor module DFRobot – OYMotion (Product Code: SEN0240) was employed to acquire electromyographic signals generated by muscle contractions of the user. The overall structure of the SEN0204 sensor module is illustrated in Fig. 1. This analog sEMG module, co-developed by DFRobot and OYMotion, integrates essential functional blocks including signal amplification, noise filtering, and primary signal conditioning.

One of the most notable advantages of this module is its capability to operate with dry metal electrodes, eliminating the need for conductive gel typically required by conventional medical electrodes. This feature significantly simplifies the setup process, enhances durability, and improves user convenience, particularly in non-invasive human–machine interaction (HMI) applications. The use of dry electrodes allows for flexible deployment on both static and dynamic muscle regions while maintaining reliable signal quality.

The sensor is capable of amplifying small sEMG signals in the range of ±1.5 mV up to 1000 times. It utilizes differential input combined with an integrated analog filtering stage to effectively suppress noise, particularly power line interference at 50/60 Hz. The sensor operates optimally within a frequency range of 20 Hz to 500 Hz, which corresponds to the primary spectral band of sEMG signals. The output is provided as an analog voltage signal with a reference level of 1.5 V and a swing range from 0 to 3.0 V, making it well-suited for digitization via analog-to-digital converters (ADCs) in microcontroller-based embedded systems.

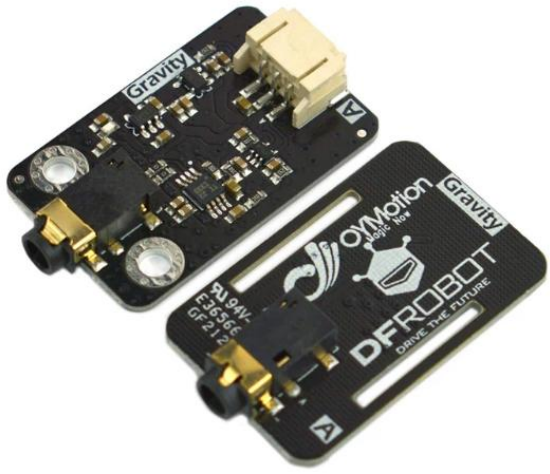


Fig. 1. SEN0204 analog EMG sensor by OYMOTION [24].

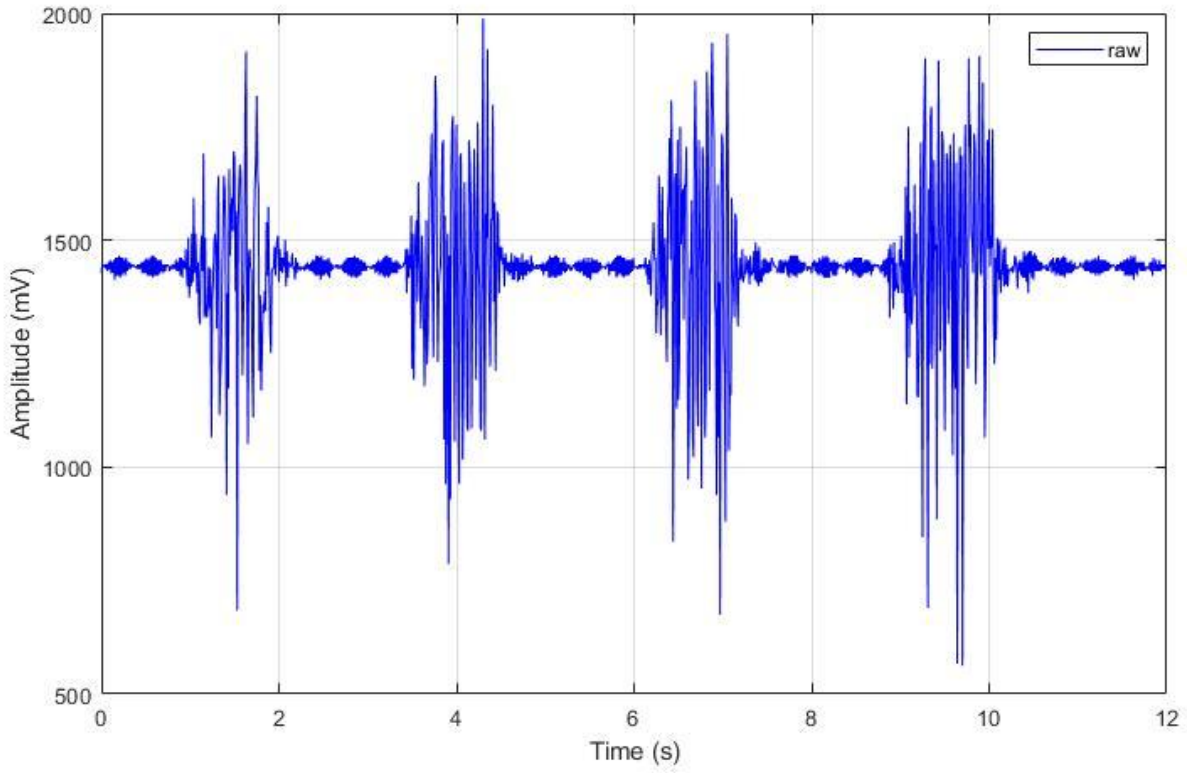


Fig. 2. An illustration of a raw sEMG signal.

Fig. 2 illustrates a raw sEMG signal acquired from the SEN0240 sensor using a 10-bit ADC. The signal was sampled at a frequency of 1000 Hz. The output amplitude fluctuates within the range of approximately 500 mV to 2000 mV, with an average baseline (offset) value around 1.5 V (1500 mV), consistent with the sensor's technical specifications. The signal clearly demonstrates alternating phases of muscle contraction and relaxation, characterized by high-amplitude fluctuations during active periods and near-flat regions during rest. Notably, strong muscle contractions occur at approximately 1.5s, 4.5s, 7s, and 9.5s, with signal amplitudes spiking significantly above the baseline level. During the resting intervals, the signal oscillates mildly around 1.5 V, indicating minimal muscle activity. The presence of power line interference (50 Hz) or high-frequency noise components is noticeable, particularly in the low-activity segments.

*2) Signal preprocessing*: The surface electromyography (sEMG) signal was acquired from the SEN0240 sensor using a three-electrode configuration: two electrodes placed over the muscle and one reference (GND) electrode. The output signal is in the form of an analog voltage within the 0–3.0 V range, with a baseline level of approximately 1.5 V. The amplitude fluctuations of the signal reflect the level of muscle activity.

A sampling frequency of 1000 Hz was selected, which is suitable for the effective bandwidth of sEMG signals (20 to 500 Hz) [25], [26] and satisfies the Nyquist sampling theorem to prevent aliasing. After acquisition, the signal values were converted from raw ADC units to millivolts (mV) to facilitate further processing.

Raw sEMG signals are often contaminated by various noise sources, such as power line interference during acquisition and poor electrode-skin contact, which introduces additional artifacts [27]. Therefore, a signal pre-processing stage is essential. De Luca et al. [28] emphasized the use of high-pass filters to eliminate low-frequency noise, recommending a cutoff frequency of 20 Hz for natural movements and higher values for intense physical activity. Conversely, a low-pass filter with a cutoff frequency between 400 and 500 Hz is recommended. One of the most widely adopted solutions for EMG signal filtering is the use of a Butterworth band-pass filter with a typical passband ranging from 20 to 450 Hz.

In this study, the sEMG signal was pre-processed using a three-stage filtering approach. First, a high-pass filter with a cutoff frequency of 20 Hz was applied to remove low-frequency drift and DC offset while preserving relevant muscle activity components. Next, an IIR notch filter centered at 50 Hz was used to suppress power line interference, which typically appears as a dominant peak in the EMG frequency spectrum [29]. Finally, a low-pass filter with a cutoff frequency of 450 Hz was employed to eliminate high-frequency noise, including impulsive and RF interference. Both the high-pass and low-pass filters were implemented as second-order Butterworth filters to ensure a flat frequency response in the passband and minimal signal distortion. The filtering process was performed using the zero-phase filtfilt method to avoid phase delay.

*3) Overlapped sliding window segmentation*: The sEMG signal is segmented into smaller portions to facilitate time-domain feature extraction. The choice of segment length must be carefully considered: overly long segments may increase computational load, whereas segments that are too short can result in inaccurate feature extraction. In real-time applications in particular, segment lengths exceeding 200 milliseconds often require the use of overlapping techniques to ensure continuity and responsiveness in system feedback [30].

This method divides the signal into fixed-length windows (w), with each window being shifted by a smaller step size (s). This results in overlapping segments, meaning that a single signal sample may appear in multiple consecutive windows. The window length (w) determines the amount of EMG data used for feature extraction, while the step size (s) defines the temporal distance between windows and controls the sliding rate. A smaller step size leads to increased overlap and provides more data for analysis [37]. Selecting an appropriate window and step size is a crucial factor. Larger window sizes allow for more comprehensive information capture and lower variability in extracted features. However, excessively large windows can introduce perceptible delays, which may negatively impact the user experience when using assistive devices. Therefore, as suggested in [38], the optimal window length is typically in the range of 150 ms to 250 ms.

In this study, the window size (w) is set to 200 ms, and the step size (s) is set to 50 ms, as illustrated in Fig. 3. With a sampling frequency of 1 kHz, each window corresponds to 200 samples. As each window shifts by 50 samples, there is a 75 per cent overlap between consecutive windows.

This sliding window-based segmentation effectively captures the temporal characteristics of the sEMG signal, thereby enhancing the accuracy and robustness of the gesture recognition system [36].

*4) Feature extraction*: The sliding window-based signal analysis method not only ensures the ability to continuously monitor muscle activity over time but also facilitates the subsequent feature extraction stage. The segmented signal obtained through this technique exhibits a stable format and well-defined structure, which enhances the accuracy of feature computation and meets the real-time requirements of human–machine interactive robotic control systems.

Extracted features can be categorized into time-domain, frequency-domain, or time–frequency domain features [31]-[34]. Frequency-domain features help identify the frequency components of muscle activity, providing insights into muscle activation levels and the ability to suppress noise. The signal is transformed into the frequency domain using the Discrete Fourier Transform (FFT). Commonly used frequency-domain features include Mean Frequency (MNF), Median Frequency (MDF), Mean Power Frequency (MNP), Peak Frequency (PKF), and Total Power (TTP) [Phinyomark, Yinfeng]. The combination of information from both time and frequency domains is defined as time–frequency features. Common techniques used in this category include Discrete Wavelet Transform (DWT), Short-Time Fourier Transform (STFT), and Wavelet Packet Energy [34].

Frequency-domain features are often used to study muscle fatigue or in motor unit analysis; however, they are generally not suitable for EMG signal classification [32], [33]. In addition, the high computational load may pose challenges for real-time control applications. Time-domain feature extraction, by contrast, is a widely adopted and effective approach for characterizing sEMG signals with low computational complexity, making it well-suited for real-time control systems. These features are directly derived from the amplitude values of the signal within each sliding window.

In this study, the selected time-domain feature includes:

*a) Mean absolute value (MAV)*: The average of the absolute values of the EMG signal within a window, representing the intensity of muscle activity.

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{1}$$

*b) Waveform length (WL)*: The cumulative length of the EMG signal waveform within a segment, representing the signal's variability and complexity [35].

$$WL = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{2}$$

*c) Variance (VAR)*: The statistical dispersion of the EMG signal within a segment, reflecting its energy level.

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^{\,2} \tag{3}$$

*d) Zero crossing (ZC)*: The number of times the EMG signal amplitude crosses the zero-voltage level within a segment. To avoid counting low-voltage fluctuations or background noise, a threshold condition is implemented. The calculation is defined as:

$$ZC = \sum_{i=1}^{N-1}[\mathrm{sgn}(x_i \times x_{i+1}) \cap |x_i - x_{i+1}| \geq threshold] \tag{4}$$

sgn(x) = 1, if x ≥ threshold

sgn(x) = 0, otherwise

*e) Slope Sign changes (SSC)*: This feature is used to represent the frequency-related information of the EMG signal. It counts the number of times the slope of the signal changes sign, which helps detect abrupt variations and transitions in the signal.

$$SSC = \sum^{N-1}[\, f[(x_i - x_{i-1}) \times (x_i - x_{i-1})]] \tag{5}$$

f(x) = 1, if x ≥ threshold

f(x) = 0, otherwise

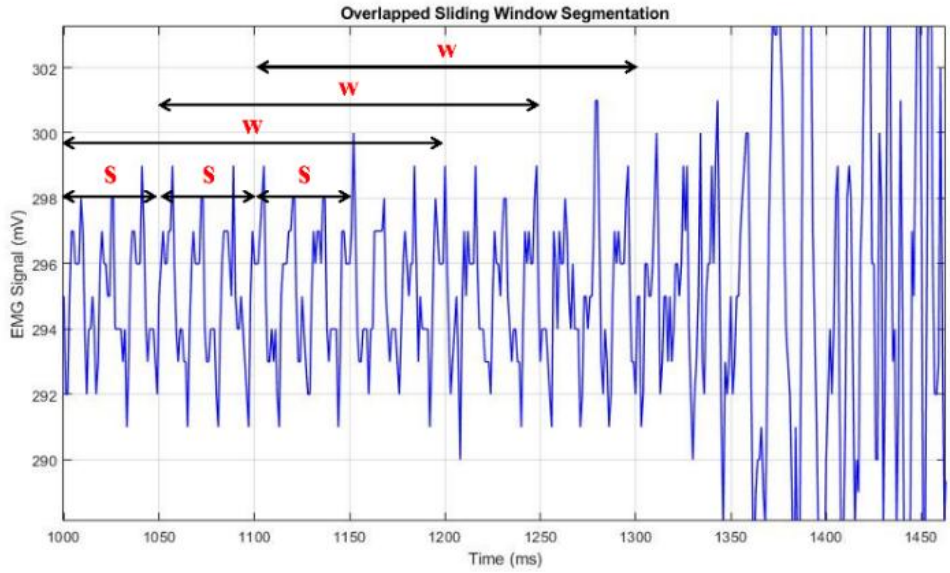


Fig. 3. Window segmentation of the sEMG signal.

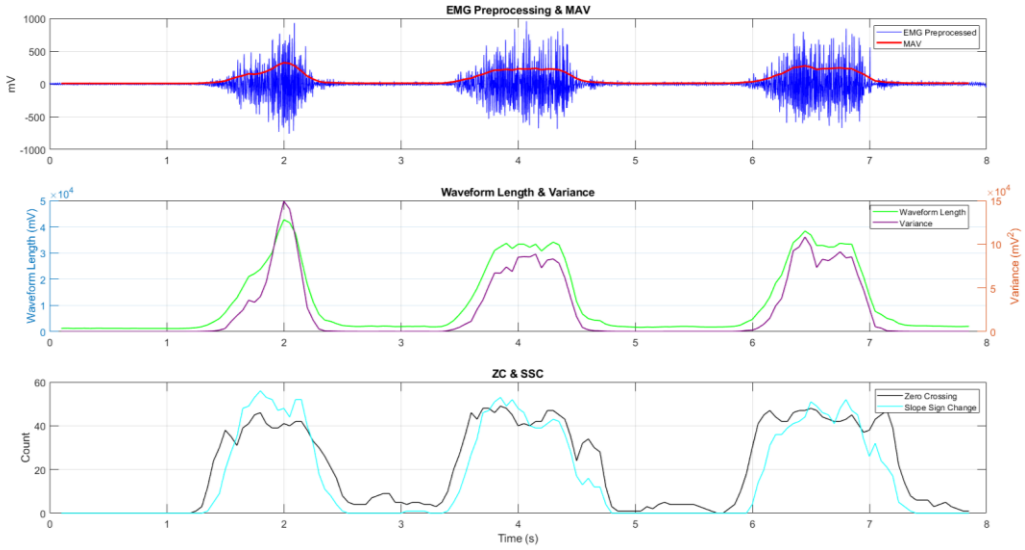


Fig. 4. An example of an EMG signal recorded with MAV, WL, VAR, ZC and SSC features.

During the sEMG signal analysis as shown in Fig. 4, time-domain features are extracted to characterize muscle activity. The Mean Absolute Value (MAV) reflects the level of muscle contraction through the signal amplitude. Waveform Length (WL) and Variance (VAR) indicate the signal's complexity and variability, while Zero Crossing (ZC) and Slope Sign Change (SSC) provide insights into the frequency of waveform transitions. These features enable clear discrimination between rest and contraction states, forming a foundation for motion recognition and robotic control.

### *B. Application in Artificial Hand Control*

*1) Sensor location*: The placement of EMG electrodes plays a critical role in distinguishing the performance across different finger movement patterns. Achieving this requires a solid understanding of the underlying muscular structure responsible for finger control, particularly when selecting optimal sEMG electrode positions. Within the forearm region, two major muscle groups are primarily involved in finger movement control: the flexor muscles and the extensor muscles. These muscle groups are situated on both sides of the wrist and run along the length of the forearm.

The flexor muscles, located on the anterior side of the forearm, such as the Flexor Digitorum Profundus (FDP) and Flexor Digitorum Superficialis (FDS), are responsible for flexing the wrist and fingers. In contrast, the extensor muscles, situated on the posterior side, including the Extensor Digitorum

(or Extensor Digitorum Communis – EDC) and Extensor Digiti Minimi (EDM), control the extension of these joints. These two muscle groups operate in opposition: when one contracts, the other relaxes. Therefore, to effectively capture EMG signals associated with finger activity, it is essential to position sEMG electrodes over both the flexor and extensor muscle regions.

Fig. 5 illustrates the electrode placement strategy. Electrode position 1 targets the activity of the ring and little fingers; position 2 corresponds to the index and middle fingers; and position 3 captures movements of the thumb. The electrodes are aligned centrally along the muscle fibers and spaced approximately 2.5 cm apart to ensure optimal signal acquisition.

*2) Artificial hand control*: Fig. 6 illustrates the overall control diagram of the artificial hand system based on surface electromyography (sEMG) signals. The system utilizes three sEMG sensors placed on the user's arm to acquire bioelectrical signals generated by muscle activity. These signals are preprocessed to remove noise and normalized before feature extraction. The extracted features are then classified to identify the user's intended motion. The classification results are used as input for the controller to actuate the robotic hand accordingly. A human-machine interface (HMI) is integrated to visualize sEMG signals and system status in real-time. Additionally, the system supports communication with a computer for monitoring, data analysis, and parameter adjustment.

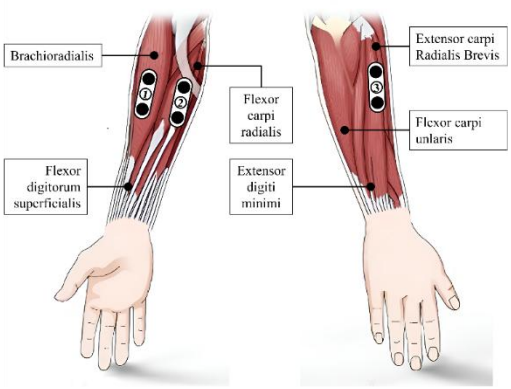


Fig. 5. Human hand muscle structure and electrode placement.

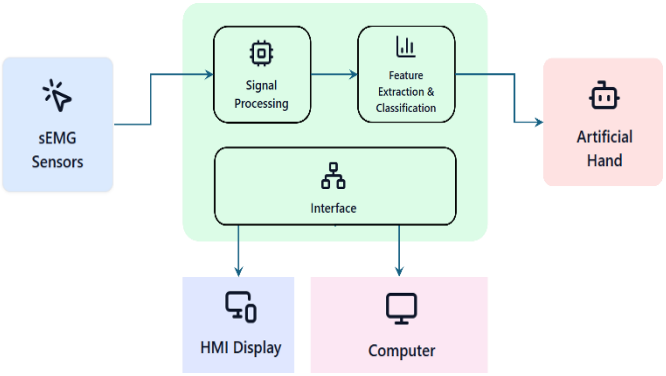


Fig. 6. The control system overview diagram.

## III. Experimental Results

To evaluate the effectiveness of the proposed EMG-based control system, both signal processing results and real-time robotic hand responses were analyzed. Fig. 7 illustrates the EMG signals from three channels, along with the extracted features: Mean Absolute Value (MAV), Variance (VAR), and Waveform Length (WL). These features were computed in real-time over a sliding window and are visualized to correlate with the four distinct muscle activation segments corresponding to different gestures.

The MAV feature showed consistent performance in highlighting the onset and duration of muscle activation across all channels. On the other hand, VAR and WL provided additional sensitivity in distinguishing gestures with similar EMG amplitudes but different signal complexities. The combination of these three features thus offers a robust representation of muscle activity, suitable for classifying and interpreting user intentions.

Fig. 8 demonstrates the practical implementation of the control system, where each user gesture (e.g., wrist extension, flexion, or grasping motion) was successfully translated into the corresponding movement of the robotic hand. The robotic hand responded in real-time with clear alignment to the user's intended actions.

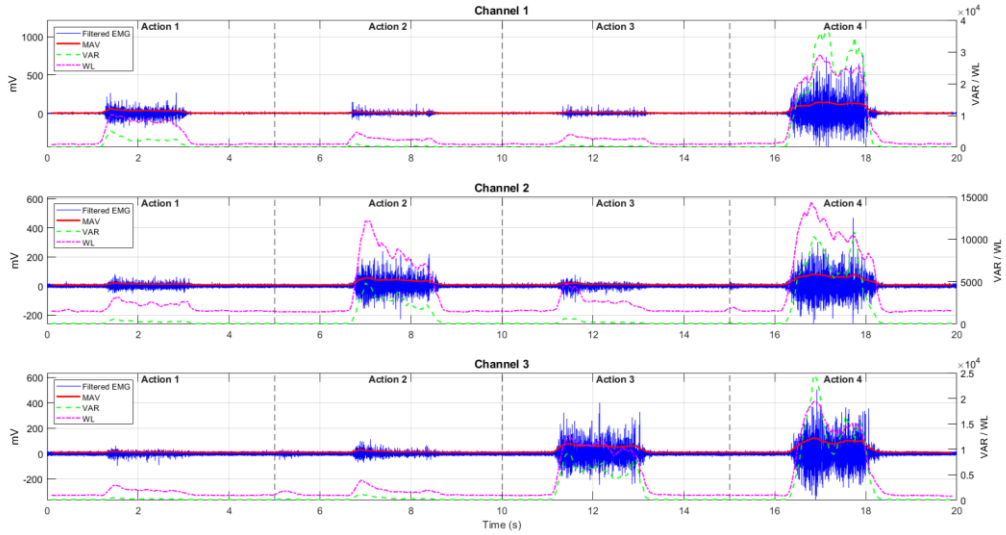


Fig. 7. EMG signals and extracted features during different hand motions.

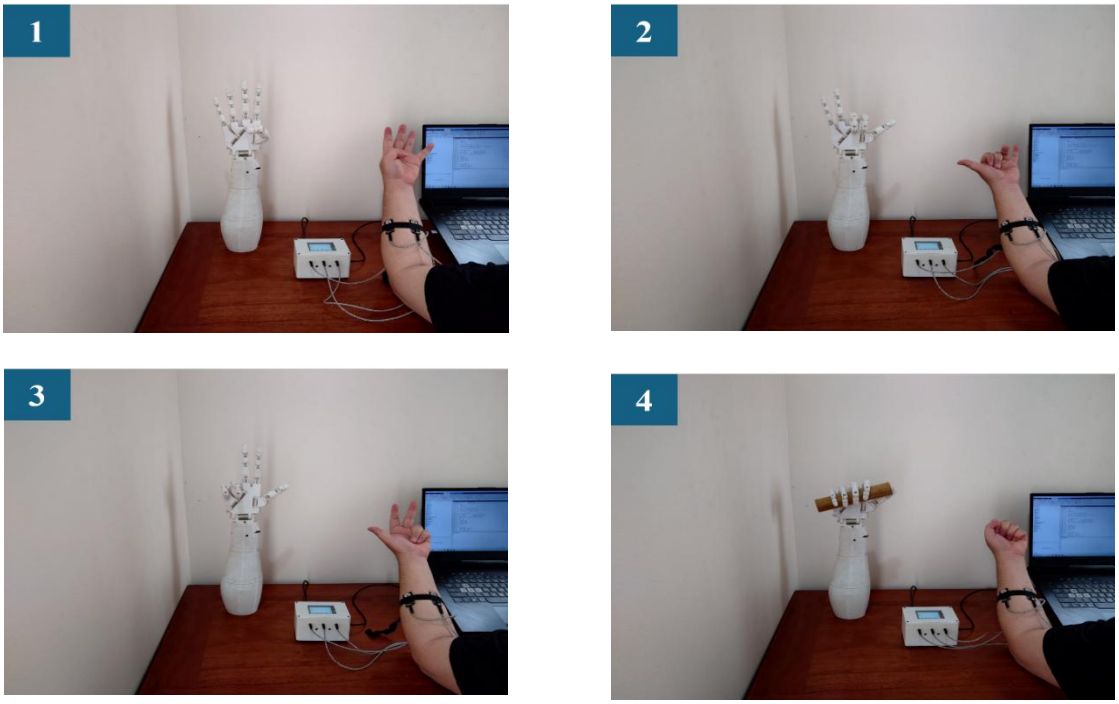


Fig. 8. Real-time EMG-based control of a prosthetic hand using four distinct hand gestures.

## IV. Discussions

The experimental results illustrated in the previous section confirm that the EMG signals acquired from the forearm can effectively control a wearable robotic hand in real time. The proposed system offers low latency and high responsiveness, critical for natural human-machine interaction.

Furthermore, the feature extraction and segmentation pipeline proved reliable in isolating intentional movement from resting or noise-dominant periods. Although the system currently operates on predefined gestures, it provides a foundation for further development involving real-time classification algorithms such as Support Vector Machines or Neural Networks.

Despite the promising results, this study has some limitations. First, the system currently relies on a limited number of predefined hand gestures, which restricts its general applicability. Second, the experiment was conducted with a small number of participants under controlled conditions, which may not fully represent real-world variability in sEMG signals across different users or usage scenarios. Additionally, although the proposed method is optimized for embedded implementation, further evaluation on various hardware

platforms is needed to assess performance consistency. Addressing these limitations will be a key focus in future work.

## V. CONCLUSION

This study presents a preliminary investigation into the processing of surface electromyography (sEMG) signals for the control of wearable robotic hand systems. A foundational signal processing framework, suitable for real-time applications, was developed, encompassing filtering, window-based segmentation, and the extraction of relevant time-domain features, including Mean Absolute Value (MAV), Waveform Length (WL), Variance (VAR), Zero Crossing (ZC), and Slope Sign Changes (SSC).

The implementation of sliding window segmentation and feature extraction from strategically positioned sEMG electrodes over both flexor and extensor muscles demonstrated efficacy in capturing muscle activity associated with finger movements. These extracted features serve as input vectors for subsequent classification and control algorithms.

This work constitutes an initial phase in the development of a comprehensive human–machine interface. It establishes a basis for future research focused on the integration of advanced classification algorithms, such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), or deep learning methodologies, for accurate gesture recognition and adaptive robotic hand control. The findings of this study are anticipated to contribute to the advancement of intuitive, responsive, and user-centered assistive robotic systems, particularly for rehabilitation and prosthetic applications.

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# Enhancing Match Detection Process Using Chi-Square Equation for Improving Type-3 and Type-4 Clones in Java Applications

Noormaizzattul Akmaliza Abdullah[1], Al-Fahim Mubarak-Ali[2], Mohd Azwan Mohamad Hamza[3], Siti Salwani Yaacob[4]
Faculty of Computing, Universiti Malaysia Pahang Al-Sultan Abdullah, Pekan, Pahang, Malaysia[1, 3, 4]
Centre For Artificial Intelligence & Data Science, Universiti Malaysia Pahang Al-Sultan Abdullah, Lebuh Persiaran Tun Khalil, Yaakob, 26300 Gambang, Kuantan, Pahang[2]

***Abstract*—Generic Code Clone Detection (GCCD) is a code clone detection model that use distance measure equation, enabling detection of all types of code clones, naming clone Type-1, Type-2, Type-3 and Type-4 in Java programming language applications. However, the detection process of GCCD did not focus on detecting clones of Type-3 and Type-4. Hence, this paper suggested two experiments to incorporate enhancements to the GCCD in order to improve the detection rate of clone Type-3 and clone Type-4. The implementation of Chi-square distance in the match detection process produced a significant result increase in the experiment specifically on clones Type-3 and Type-4, in comparison with the Euclidean distance in GCCD, which allows the increase of detection rate due to the dissimilarity of the distance measures. Based on the results, the suggested enhancement using Chi-square distance on match detection process outperforms GCCD in terms of improving code clone detection results based on clone Type-3 and Type-4, as the objectives for each experiment are carried, contributes to the research on improving the code clone detection result.**

***Keywords*—Code clone detection; distance measure; Java language; Chi-square; computational intelligence***

## I. INTRODUCTION

The practice of copying code is known as code cloning and the clone being duplicated is a code clone [1]–[3]. 60% developers went on searching code examples every day as to reduce the development time process [4] and which leads to code cloning. However, the integrity of certain developer cannot be underestimated as code examples could be implemented to the system instead of coding a new code fragment which lead to code cloning. Cost and programmer's limitation, templating and many more could also be the reasons for code cloning [4]–[6]. These reasons for code cloning could lead to drawbacks on software development and maintenance. The increase of maintenance cost, bug propagation, computational complexity and vulnerability proneness [5]–[8]. The inadequacy of programming language could also affect the code cloning [9], [10]. Java is a free programming language that developed open-source software applications. A study mentioned that 6% of 512000 lines of codes in Java applications are code clones [11]. The study concluded that the reason of code clones was the stake-holder's demand and deficiency in Java generic modules.

Code clones are generally categorized into four distinct types [12]–[14]; Type-1, Type-2, Type-3 and Type-4 (Fig. 1). Clone Type-1 is known for exact matches. These are code fragments that are identical, except for differences in whitespace and comments. Type-1 clones are the simplest to detect since they involve straightforward duplication without any modifications to the actual code logic. Clone Type-2 is renamed clones. In these clones, the code fragments are identical except for variations in identifiers, literals, types, or other superficial changes. While the overall structure and logic remain the same, these changes can make detection more complex than Type-1 clones. Clone Type-3 is modified clones. These are more complex clones where the duplicated code has undergone modifications such as adding or removing lines of code, altering control structures, or making other significant changes. Despite these modifications, the underlying logic or functionality of the code remains similar, making Type-3 clones challenging to detect. Finally, clone Type-4, the semantic clones. The most difficult to detect, Type-4 clones involve code fragments that perform the same functionality but are implemented using entirely different syntax or structures. These clones require deep semantic analysis to identify, as they do not share visible structural similarities with the original code.

Several major code clone approaches are prior to undertaking. The six major code clone approaches include text-based approaches, token-based approaches, metric-based approaches, tree-based approaches, graph-based approaches, and hybrid approaches. However, most approaches are incapable of recognizing all code clones [15]. For instance, token-based approach code detection tool such as NiCad [16],[17] detect the lexical part of the source code without considering the semantic information, which then prompted a poor detection result of clone Type-3 [18]. As a response, a code clone detection model was built for detecting code clones effectively. A model for the detection of the code clone incorporates structural process that combine several approaches or tools for the detection of clones. Several models that have existing in the code clone domain are the Generic Clone Model [19], the Generic Pipeline Model [20], Unified Clone Model [21], as well as the Generic Code Clone Detection (GCCD) Model [11]. Multiple researchers studied these four models in order to develop an effective code clone detection model. For instance, an enhancement was made in a

study on Generic Pipeline Model whereby they concatenated the source code file through Divide and Conquer method to enhance the load processing speed, by dividing the file into sub files [22]. They managed to decrease the model's runtime performance and increase the model's performance fully. Another study is on the GCCD model where they enhanced the pre-processing and parameterization process of GCCD [9], [23]. They managed to reduce the pre-processing rules and finding the best weightage to produce a better code clone detection model.

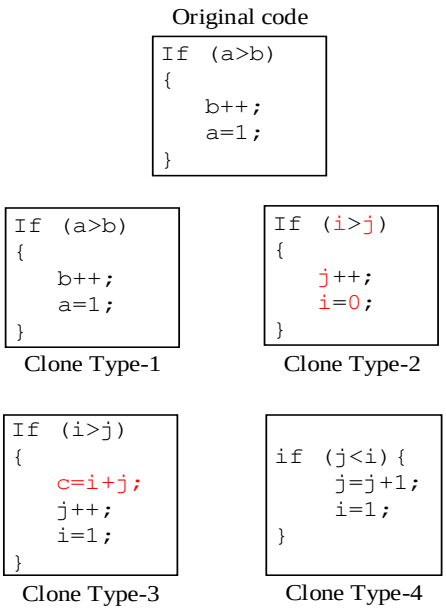


Fig. 1. Example of code clone Type-1, Type-2, Type-3 and Type-4.

The preliminary goal of this work is for enhancing the GCCD in order to produce a reliable code clone detection result, specifically Type-3 and Type-4. Therefore, this work will focus on;

- The experiment is an enhancement on match detection process using different distance measure equation such as Manhattan distance, Squared Euclidean distance, Half-squared Euclidean distance, Chi-square distance, in order to find the highest detection result of Type-3 and Type-4.
- The comparative analysis of the result between GCCD as an existing model and the proposed enhancement towards GCCD in terms of Type-3 and Type-4.

## II. Related Works

Generic Code Clone Detection (GCCD) is a tool commenced for an aim to detect code clones in Java language application [11]. This model was developed targeting to detect code clone Type-1, Type2, Type-3 and Type-4. The purpose of GCCD is to provide a generality approach for identifying all sorts of code clone. GCCD is constructed with a structure of five processes (Fig. 2). The processes are pre-processing process, transformation process, parameterization process, categorization process and match detection process.

### A. Pre-Processing Process

This process standardizes the source code as input for the detection process. There are five pre-processing rules applied to the source code in order to remove unnecessary elements that may conflict with the code clone detection result. The first pre-processing rule removes packages and import statements from the source code. Then, the second pre-processing rule is followed by removing comment lines as the comments are considered as instruction or guidance to the programmer only, which is not conflicting with the source code. The third pre-processing rule removes empty lines, which normally do not hold any source code and act as a method to visualize a clean look in coding. After that, the code is then regularized in the fourth pre-processing rule by replacing all function access modifier to public access modifier. This part of the rule act as a constant value for producing metrics in parameterization process. The fifth rule is to convert all uppercase letters in the original source code to lowercase letters for reducing the difference for detecting code clones. The essence of the source code has been filtered and the source code has become source unit.

### B. Transformation Process

This process converts the source units into measurable units by substituting the source units with numerical value. The source unit is substituted one by one based on the position of alphabets. For instance, the alphabet *p* is substituted to 16 as the numerical value. Taking an example of word of the source unit from the Fig. 3, we can see that 'public' is substituted with value 162102120903.

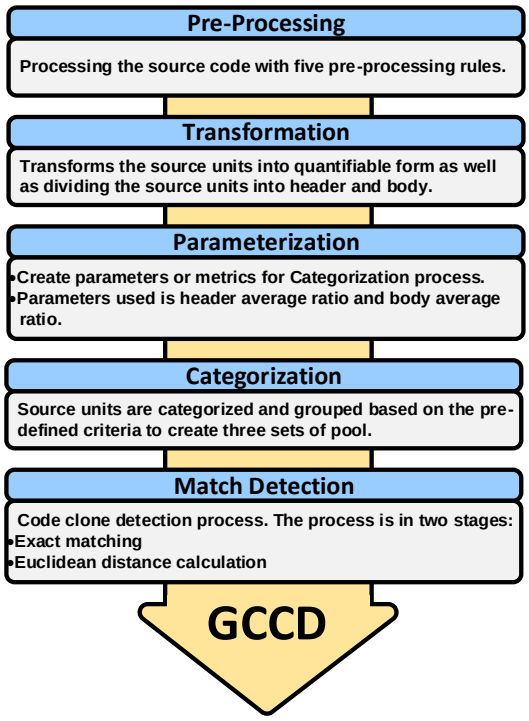


Fig. 2. Structure process of GCCD.

This substitution method allows the source unit to be valued as measurable unit. After that, the measurable source units are divided into header (*h*) and body (*b*) to become a transformed source unit. Header is the first line of a function source code and body is the next line of a function source code after the first line. In the Fig. 3, the lines of source unit public *boolean hasmoreelements* is the first line of function where this line is considered as the header. The rest of the lines are considered as body. This unit will become transformed source unit which is the output of this process.

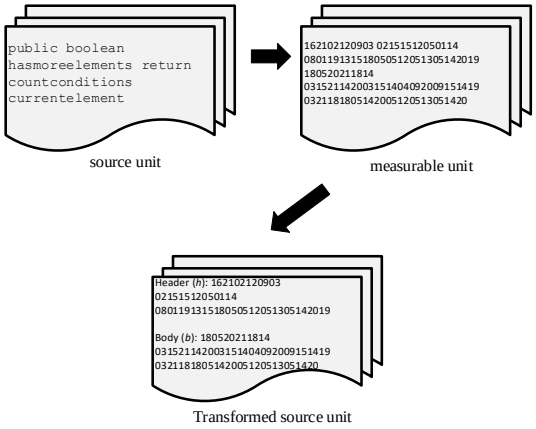


Fig. 3. Snippets of source unit is substituted and grouped to become a transformed source unit.

### C. Parameterization Process

This stage will set up the parameters that would be utilized throughout the categorization process from the transformed source unit (*TSU*). The *TSUs* are in the form of transformed source unit header (*TSUh*) and transformed source unit body (*TSUb*). The parameters involved are average ratio header and average ratio body. Table I shows the parameters involved in getting the average ratio header and body and its description. In order to gain average ratio header and average ratio body, *TSU*s are calculated to gain ratio header along with ratio body. Both ratios require *TSU* to be calculated using this:

$$TSUh_n = A_1 + A_2 + A_3 + \cdots + A_n \quad (1)$$

$$TSUb_n = B_1 + B_2 + B_3 + \cdots + B_n \quad (2)$$

Since all functions have been transformed into a standardize value of public, all the source units have similar access modifier value. Therefore, these *TSU*s are divided with public access modifier weightage value (*P*). The *P* is gain through the substitution of word 'public' into162102120903 as the weightage value. The calculation of ratio header and ratio body can be visualized in equation:

$$Rh_n = \frac{TSUh_n}{P} \quad (3)$$

$$Rb_n = \frac{TSUb_n}{P} \quad (4)$$

where $n$ = 1, 2, 3. After ratio header and ratio body is calculated, the process is tried with finding average ratio header together with average ratio body for each source unit. Ratio header and ratio body is divided with count header as well as count body respectively using this equation:

$$AVRh_n = \frac{Rh_n}{Ch_n} \quad (5)$$

$$AVRb_n = \frac{Rb_n}{Cb_n} \quad (6)$$

From here, the output of transformation process is represented in metric form as parameters.

TABLE I. DESCRIPTION OF PARAMETERS INVOLVED IN PARAMETERIZATION PROCESS

| Parameters | Description |
|---|---|
| Transformed source unit header (*TSUh*) | Value of transformed source unit in header |
| Transformed source unit header (*TSUb*) | Value of transformed source unit in body |
| Ratio header (*Rh*) | The ratio of headers of the transformed source units |
| Ratio body (*Rb*) | The ratio of body of the transformed source units |
| Count header (*Ch*) | Code count of source code header in the source units |
| Count body (*Cb*) | Code count of source code body in the source units |
| average ratio header (*AVRh*) | The average ratio of header (*h*) |
| average ratio header (*AVRb*) | The average ratio of body (*b*) |

### D. Categorization Process

The categorization process occurs by comparing between two *TSU*. Assuming there are *TSUX* and *TSUY*, they are categorized into the first pool as they have the similar *AVRh*. The process of categorizing *TSU* into the first pool runs until every *TSU* with similar *AVRh* is grouped. Then, the *TSU* continue its categorization process together with the remaining from first pool to group *TSU* with similar *AVRb* into the second pool. Once the categorization process reaches its ends for the second pool, the categorization process moves to the third pool, grouping the remainder of *TSU* that cannot match to the first pool and the second pool. This process produces three pools as the output, bringing them to the final process which is match detection.

### E. Match Detection Process

Finally, the pools are screened for Type-1, Type-2, Type-3, and Type-4 clones using match detection process. There are two stages of match detection for detecting code clones. The first stage is exact matching where clone Type-1 and clone Type-2 are detected from the first two pools. The match is considered as Type-1 when two average ratio header and body are identical, following the next pair of matches during the first two pool is processed. As for clone Type-2, certain pairs compared is considered as clone Type-2 when they have similar *AVRhx* and *AVRhy* but different *AVRbx* and *AVRby*, or vice versa. The second stage implements the Euclidean distance measure formula to determine the remnants from the first two pools and the third pool. Assuming the calculation involves two source units' *X* and *Y*. Each source unit consists of average ratio header and average ratio body. The formula of Euclidean distance (ED) is as follows:

$$ED = \sqrt{(AVRhX - AVRhY)^2 + (AVRbX - AVRbY)^2} \quad (7)$$

The outcome from Euclidean distance calculation is then determined its value. The value that fits within 0.85 and 1.00 is

classified as Type-3, while the remainder value is classified as Type-4.

## III. Proposed Enhancement

The proposed enhancements are focusing on two processes from GCCD, which are the match detection process. The dataset for these experiments is similar to the dataset from GCCD, which is Java applications of Bellon's benchmark dataset [28]. This dataset is a benchmark in code clone domain that consists Java applications with medium size to larger size. It also provides the details to the four Java applications involved.

Previously in GCCD, the process of match detection implements Euclidean distance on to the three pools from the categorization process, in order to gain the clone Type-3 and clone Type-4. Once calculated, the value that falls between the ranges 0.85 to 1.00 is considered as clone Type-3 and suchlike is considered as clone Type-4. In comparison to previous GCCD outcomes, the aim of the first experiment is to produce a greater detection result for code clone Type-3 and code clone Type-4, by utilizing different distance measures [24]. Four distance measures were discovered for which the parameters generated from prior processes of GCCD could be applied to achieve. The distance measures are referred in Table II Manhattan distance [25], Squared Euclidean distance [26], Half-squared Euclidean distance [27], and Chi-square distance [28].

TABLE II. Equations Involved in Experiment 1

| Equation Name | Equation |
|---|---|
| Manhattan distance | $d(x,y) = \sum_{i=1}^{n} \mid x_i - y_i \mid$ |
| Squared Euclidean distance | $d^2(x,y) = \sum_{i=1}^{n} (x_i - y_i)^2$ |
| Half-squared Euclidean distance | $d^2(x,y) = \sum_{i=1}^{n} (x_i - y_i)^2$ |
| Chi-square distance | $\chi(x,y) = \sqrt{\frac{1}{2}\sum_{i=1}^{n} \frac{(x_i - y_i)^2}{(x_i + y_i)}}$ |

Manhattan distance calculates the absolute difference between corresponding components of two vectors, offering a simple yet effective way to assess similarity when the changes between code fragments are predominantly additive or subtractive. Squared Euclidean distance is an extension of the standard Euclidean distance, this formula squares the differences between corresponding components before summing them, placing greater emphasis on larger deviations, which may be particularly useful in distinguishing more pronounced differences in code structure. Meanwhile, half-squared Euclidean distance measures halves the squared differences, providing a balance between the sensitivity of the Squared Euclidean Distance and the simplicity of the Manhattan Distance, potentially offering a more nuanced assessment of similarity. Finally, Chi-square distance, a statistical measure that compares the observed and expected frequencies of occurrences, this formula is particularly suited for detecting differences in distributions, making it a promising candidate for identifying Type-4 clones where the code fragments may function similarly but differ significantly in their structural composition. The aforementioned equations will replace the Euclidean distance in the match detection process. The pseudocode 1 shows the pseudocode on the implementation of Chi-square distance into GCCD as an example.

**Pseudocode:** Match Detection Process using Chi-square distance

Pool 1, $PL_1$
Pool 2, $PL_2$
Pool 3, $PL_3$
Chi-Square Distance, *CSD*
Average ratio header, [$AVRh_1, AVRh_2, AVRh_3, \ldots AVRh_n$]
Average ratio body, [$AVRb_1, AVRb_2, AVRb_3, \ldots AVRb_n$]

```
Read [AVRh1, AVRh2, AVRh3, ... AVRhn] and [AVRb1, AVRb2, AVRb3, ... AVRbn] in PL1 and PL2
    Compare AVRh1 and AVRb1 with AVRh2 and AVRb2 using exact matching technique
        If AVRh1 and AVRb1 are same with AVRh2 and AVRb2
            Group as Type-1
        Else If AVRh1 and AVRh2 are same but AVRb1 and AVRb2 are different
            Group as Type-2
        Else If AVRh1 and AVRh2 are different but AVRb1 and AVRb2 are same
            Group as Type-2
        Else
            AVRh1 and AVRh2 are different but AVRb1 and AVRb2 are different
Move into PL3
Read remaining [AVRh1, AVRh2, AVRh3, ... AVRhn] and [AVRb1, AVRb2, AVRb3, ... AVRbn] in PL3
Apply CSD between the remaining [AVRh1, AVRh2, AVRh3, ... AVRhn] and [AVRb1, AVRb2, AVRb3, ... AVRbn]
    If distance is between 0.85 to 1.00
        Group as Type-3
    Else
        Group as Type-4
```

By using the similar assumption from Section II(E) where there are two source units *X* and *Y*, the calculation of the match detection process can be visualized in the chi-square equation where the average ratio header and average ratio body is used:

$$CSD = \sqrt{\frac{1}{2}\left(\frac{(AVRhX - AVRhY)^2}{(AVRhX + AVRhY)} + \frac{(AVRbX - AVRbY)^2}{(AVRbX + AVRbY)}\right)} \quad (8)$$

## IV. Result Analysis

The result from the experiment is recorded in two elements namely overall total clone pairs in Java applications and total clone pairs based on clone types. This section is divided into three subsections where the first subsection describes the result of overall total clone pairs and the second subsection is about the total clone pairs based on clone types, which resulted from the experiment. The final subsection analyzes and discusses the outcome from the result to pinpoint the difference between the existing GCCD and the enhancement made to GCCD.

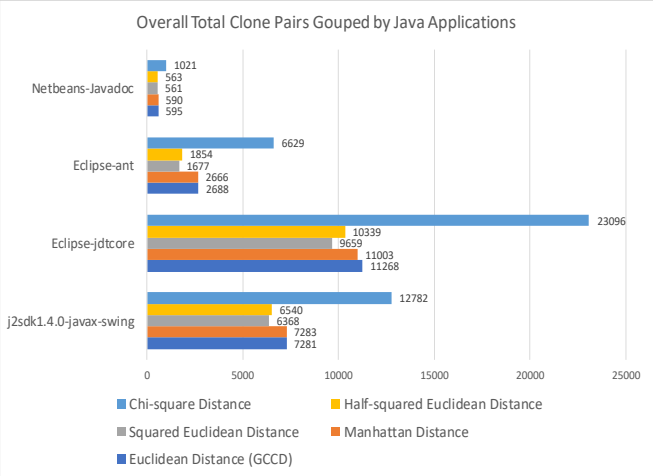


Fig. 4. Overall total clone pairs based on java applications from bellon's benchmark data.

### A. Overall Total Clone Pairs in Java Applications

Fig. 4 illustrate the results of overall total clone pair in Java applications. The first Java application is j2sdk1.4.0-javax-swing. Based on data presented, Chi-square recorded the most total clone pair with 12782 clone pairs. The second most total clone pair is from Manhattan distance with a total of 7283 clone pairs. This puts the difference between the most clone pairs and the second-most with a total of 43.02%. Thirds go to the Euclidean distance with a total of 7281 clone pairs. This total clone pair is lower by 43.04% from the highest total clone pair by Chi-square distance. Total clone pair from Half-squared Euclidean distance recorded the fourth with a total of 6540 clone pairs. The difference between Half-squared Euclidean distance total clone pairs and the highest total clone pair is 48.83%. J2sdk1.4.0-javax-swing has lowermost total clone pair detected by Squared Euclidean distance with 6368 clone pairs. It is 50.18% less than the highest total clone pair by Chi-square distance.

The second Java application for detecting overall total clone pair is Eclipse-jdtcore. The top result for total clone pair is by the Chi-square distance with a total of 23096 clone pairs. The next in order is by Euclidean distance with a total of 11268 clone pairs. The gap between the highest and the second-highest overall total clone pair is 51.21%. Manhattan provides the third-most total clone pair with 11003 clone pairs. This is 52.36% lower than the highest overall total clone pair detected in Eclipse-jdtcore. The fourth result of total clone pair is Half-squared Euclidean distance with 10339 clone pairs. The difference between overall total clone pair from Half-squared Euclidean distance with the most total clone pair from Chi-square distance is 55.23%. The last from Eclipse-jdtcore is by Squared Euclidean distance with a 9659 total of clone pairs. This put the difference between the lowest and the highest from Eclipse-jdtcore with a difference of 58.18%.

The third Java application is Eclipse-ant. Overall total clone pair by Chi-square distance recorded the highest value with 6629 clone pairs. The second is followed by Euclidean distance where it gained a total of 2688 clone pairs, which left the gap of 59.45%. The third for overall total clone pair of Eclipse-ant is Manhattan distance which turned in a total of 2666 clone pairs. This put a 59.78% difference between the first and the third overall total of clone pair in Eclipse-ant. The fourth for Eclipse-ant is Half-Squared Euclidean distance, which has a total of 1854 clone pairs. This is 72.03% lower than the highest overall total clone pair in Eclipse-ant, which is the Chi-square distance. The last formula that detects a total of 1677 clone pairs is Squared Euclidean distance. This has made a 74.70% gap with Chi-square distance, the highest for Eclipse-ant.

As for Netbeans-javadoc, the most prominent total clone pair is by Chi-square distance with 1021 clone pairs. The subsequent total clone pair is by Euclidean distance. It recorded a total of 595 clone pairs, leaving the gap of 41.72% lower than the highest overall total clone pair result in Netbeans-javadoc. Next, Manhattan distance set a total of 590 clone pairs. This overall total clone pair value is lower than the highest value which is 42.21% difference. The fourth total of clone pairs is Half-squared Euclidean distance with a total of 563 clone pairs. The difference between the fourth and the first value of overall total clone pair in Netbeans-javadoc is 44.86%. 561 clone pairs are the final overall total clone pair by Squared Euclidean distance. The difference between the least and the most overall total clone pair detected in Netbeans-javadoc is 45.05%.

### B. Total Clone Pairs Based on Clone Types

This part of the result is discussed based on each Java applications by Bellon's benchmark data, based on Table III.

*1) j2sdk1.4.0-javax-swing*: Table III depicted the result of total clone pairs for each Java application. In j2sdk1.4.0-javax-swing, the detected clone pairs Type-1 is by Half-Squared Euclidean distance with 892 clone pairs. The second highest value of detecting clone Type-1 is by Chi-square distance, with 891 clone pairs, preceding about 0.11% difference from the highest clone pair Type-1 value. The third highest is by Manhattan distance with 889 clone pairs. The gap difference from the highest value of clone pair Type-1 detected in j2sdk1.4.0-javax-swing is 0.34%. The fourth value of clone pair Type-1 detected in this application is 888 clone pairs by Squared Euclidean distance, with 0.45% gap difference. Finally, Euclidean distance recorded the lowest value of clone Type-1 detected by 877 clone pairs, leaving percentage difference of 1.68%. Code clone Type-2 detection clone pair for Half-Squared Euclidean distance keep as highest value recorded with 3725 clone pairs. It is then followed by Manhattan distance with 3716 clone pairs, leaving a percentage difference of 0.24%. The third most value of clone pair Type-2 detected in j2sdk1.4.0-javax-swing is by Euclidean distance with 3697 clone pairs. The percentage difference between Euclidean distance's value and the highest value of clone pair Type-2 is 0.75%. The fourth value is by Squared Euclidean distance with 3695 clone pairs and percentage difference of 0.81%. The least clone pair Type-2 detected is by Chi-square distance with 3684 clone pairs. The percentage difference is 1.10%. Meanwhile, Chi-square distance gained the highest total clone pair Type-3 with 3633 clone pairs. This was followed by Half-squared Euclidean distance with a value of 1773 clone pairs. It is 51.20% less

than the Chi-Square distance result. The third and fourth total clone pairs Type-3 are Manhattan distance (1727 clone pairs) as well as Squared Euclidean distance (1718 clone pairs), with each gap difference of 52.46% and 52.71% respectively. The lowest total clone pair Type-3 is by Euclidean distance with a total of 1710 clone pairs, leaving a 52.93% lower than Chi-square distance. Next, Chi-square Distance was the highest in j2sdk1.4.0-javax-swing code clone Type-4, with a value of 4574 clone pairs. The Euclidean distance, which detected 997 clone pairs, is the second highest for clone Type-4. It is 78.20% lower than the highest value of clone Type-4 detected. Manhattan distance is the thirds with 951 clone pairs of Type-4, a 79.21% lower than Chi-square distance. The fourth value is by Half-squared distance with 150 clone pairs (96.72%) and the least value is from Squared Euclidean distance with a value of 67 clone pairs (98.54%) for clone Type-4.

TABLE III. TOTAL CLONE PAIRS BASED ON CLONE TYPES FOR EACH DISTANCE MEASURES

| Bellon's Benchmark Data Java Applications | Clone Type | Total clone pairs based on clone types | | | | |
|---|---|---|---|---|---|---|
| | | ***ED**** *(GCCD)* | ***MD**** | ***SED**** | ***HSED**** | ***CSD**** |
| ***j2sdk1.4.0-javax-swing*** | T-1* | 877 | 889 | 888 | 892 | 891 |
| | T-2* | 3697 | 3716 | 3695 | 3725 | 3684 |
| | T-3* | 1710 | 1727 | 1718 | 1773 | 3633 |
| | T-4* | 997 | 951 | 67 | 150 | 4574 |
| ***Eclipse-jdtcore*** | T-1* | 626 | 627 | 627 | 627 | 627 |
| | T-2* | 2886 | 2884 | 2887 | 2887 | 2886 |
| | T-3* | 4265 | 3880 | 3782 | 4564 | 7576 |
| | T-4* | 3491 | 3612 | 2363 | 2261 | 12007 |
| ***Eclipse-ant*** | T-1* | 185 | 185 | 185 | 185 | 185 |
| | T-2* | 552 | 650 | 650 | 650 | 650 |
| | T-3* | 581 | 562 | 535 | 585 | 2061 |
| | T-4* | 1370 | 1269 | 307 | 434 | 3733 |
| ***Netbeans-javadoc*** | T-1* | 99 | 99 | 99 | 99 | 99 |
| | T-2* | 341 | 338 | 338 | 338 | 338 |
| | T-3* | 102 | 102 | 102 | 104 | 197 |
| | T-4* | 53 | 51 | 22 | 23 | 387 |

[a.] *T-1 = clone Type-1, T-2 = clone Type-2, T-3 = clone Type-3, T-4 = clone Type-4, ED = Euclidean Distance, MD = Manhattan Distance, SED = Square Euclidean Distance, HSED = Half-squared Euclidean Distance, CSD = Chi-square Distance

*2) Eclipse-jdtcore*: Moving forward with the second Java application, which is Eclipse-jdtcore. The overall total clone pair Type-1 detected is consistent for each distance measure with a value of 627 clone pairs. The exception is from Euclidean distance, which detected 626 clone pairs, leaving a 0.16% gap difference from other distance measure formula. In regards to clone Type-2, the highest value went to Squared Euclidean distance as well as Half-Squared Euclidean distance, with each distance measure, scored a total clone pairs of 2887. The second greatest value for Type-2 clone is by Chi-square distance and Euclidean distance (2886 clone pairs). The lowest value is by Manhattan distance (2884 clone pairs). Both with the percentage difference of 0.03% and 0.10% from the highest value. Next, the Chi-square distance gained the highest value of 7576 clone pairs Type-3 for Eclipse-jdtcore. Half-squared Euclidean distance recorded the second-highest Type-3 value of 4564 clone pairs. It is 39.76% lower than Chi-square distance. The next distance measure followed is Euclidean distance with 4265 clone pairs of Type-3, marking a 43.70% gap from Chi-square distance. The fourth and the lowest Type-3 clones are Manhattan distance (3880 clone pairs) together with Squared Euclidean distance (3782 clone pairs). The Manhattan distance and Squared Euclidean distance are 48.79% as well as 50.08% lower than Chi-square distance. Then, clone detection for Type-4 by Chi-square distance in Eclipse-jdtcore, is the highest with a total of 12007 clone pairs. This is followed by the second highest with a value of 3612 clone pairs Type-4 by using Manhattan distance. It is 69.92% lower than Chi-square distance. The third and fourth for Type-4 in Eclipse-jdtcore are recorded by Euclidean distance (3491 clone pairs) along with Squared Euclidean distance (2363 clone pairs). They have 70.93% and 80.32% lower than Chi-square distance. The lowest value of clone pair Type-4 for Eclipse-jdtcore is by Half-squared Euclidean distance, with 2261 total clone pairs and 81.17% gap difference.

*3) Eclipse-ant*: Total clone pairs Type-1 in Eclipse-ant showed concordant outcomes for every experimented distance measure which is 185 clone pairs along individually. For Type-2, the highest clone pair value detected is by each distance measure with 650 clone pairs, except for Euclidean distance with 552 clone pairs, which is 15.08% lower than the highest value. Meanwhile, Chi-square distance showed the highest total of 2061 clone pairs Type-3, followed by Half-squared distance with a total of 585 clone pairs. Half-squared distance has 71.62% lower than Chi-square distance. The third value for clone Type-3 is by Euclidean distance with a total of 581 clone pairs and 71.81% gap difference from highest value. The fourth value is by Manhattan distance with 562 clone pairs. It is 72.73% lower than Chi-square distance. The lowest value for Type-3 clones in Eclipse-ant is Squared Euclidean distance with 535 clone pairs and 74.04% lower than Chi-square distance. Next, the Chi-square distance for clone Type-4 in Eclipse-ant has the greatest value of 3733 clone pairs. The second-highest total clone pairs are 1370 clone pairs Type-4 by Euclidean distance, with 63.30% lower than Chi-square

distance. The third and fourth values are shown by Manhattan distance (1269 clone pairs) as well as Half-squared Euclidean distance (434 clone pairs). Both has 66.01% and 88.37% lower than Chi-square distance. The least value of total clone pairs Type-4 in Eclipse-ant is by Squared Euclidean distance with 307 clone pairs. It is 91.78% lower than the highest value by Chi-square distance.

*4) Netbeans-javadoc*: The Netbeans-javadoc application was also revealed to have concordant outputs when it comes to clone Type-1 for each distance measure which is 99 clone pairs. Euclidean distance recorded the highest Type-2 value with 341 clone pairs. Other distance measures detected 338 clone pairs, 0.88% lower than Euclidean distance. For Type-3, Chi-square distance recorded the highest with 197 clone pairs, followed by Half-squared distance with 104 clone pairs. It is 47.21% lower than Chi-square distance. Euclidean distance, Manhattan distance as well as Squared Euclidean distance showed the lowest which is 102 clone pairs. It has 48.22% lower than Chi-square distance. For Type-4 in Netbeans-javadoc, the Chi-square distance also showed the highest value with 387 total clone pairs. The second highest is by Euclidean distance which is 53 clone pairs (86.30%) of Type-4, followed by the third value by Manhattan distance which is 51 clone pairs (86.82%). The fourth value is 23 clone pairs by Half-squared distance and the lowest Type-4 clone value is 22 clone pairs by Squared Euclidean distance. Both distances have 94.06% and 94.32% gap difference from Chi-square distance.

## V. Discussion

The experiment is concentrating on enhancing match detection process of GCCD by substituting the Euclidean distance to different distance measures. The enhancement on match detection process should be affecting the detection result on clone Type-3 and Type-4, as clone pairs is calculated using the distance measure formula. In this experiment, Chi-square distance has shown a significant increase on the overall total clone pairs that is detected in Java applications of Bellon's benchmark data. Moreover, Chi-square distance shows an improvement in total clone pairs based on clone types, which detected the highest value for each clone Type-3 as well as Type-4 in Eclipse-ant and Netbeans-javadoc application, respectively. Chi-square distance managed to keep the similar value of total clone pairs Type-1 other distance measures in the Eclipse-jdtcore, Eclipse-ant and Netbeans-javadoc. Chi-square distance also able to maintain the similar clone pairs Type-2 value with other distance measures for Eclipse-ant and Netbeans-javadoc. However, Chi-Square is placed as the second highest total clone pairs based on clone Type-1 and the least value in j2sdk1.4.0 – javax-swing. Another difference is in Eclipse-jdtcore application, where Chi-square distance detected the second highest value of clone pair Type-2. Based on this experiment, Euclidean distance and Chi-square distance both embody the similar structure formula. Nonetheless, Chi-square distance divides the upper value with a frequency inverse using the weightage summation of both header and body. As for the difference in result on clone Type-1 and Type-2 in two of the mentioned Java applications, runtime performance during the pre-processing process and transformation process might have affected the detection result. Thus, Experiment 1 concludes that the implementation of Chi-square distance increases the clone pair detection result specifically in Type-3 and Type-4, respectively.

## VI. Conclusion

In this paper, we introduced an improvement that is to the GCCD for detecting code clones in each clone type, specifically Type-3 and Type-4, due to the earlier result from GCCD implicit the inconsistency of the clone detection result in Java applications in Bellon's benchmark dataset. The enhancement that proposed the detection result of clone pair Type-3 and Type-4 can be improved by enhancing match detection process of GCCD, through modifying the distance measures. Result from the experiment revealed that the implementation of Chi-Square provides a higher code clone detection result as the GCCD is enhanced using Chi-square distance in match detection process. The improvement can be seen specifically when it has overruled GCCD by detecting the highest clone pairs Type-3 and Type-4.

The model currently supports clone detection within Java applications as the dataset is limited to the Bellon's benchmark dataset Java application. As a future enhancement, experiment on detecting and analyzing clone pairs in Python applications will be conducted.

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# Transforming Internal Auditing: Harnessing Retrieval-Augmented Generation Technology

Professor Olive Stumke, Mr Fanie Ndlovu
Faculty of Accounting and Informatics-Department of Auditing and Taxation
Durban University of Technology, Durban, South Africa

***Abstract*—The advent of cloud-based Generative AI models, such as ChatGPT, Google Gemini, and Claude, has created new opportunities for improving education through real-time, adaptive learning experiences. Despite their widespread use globally, their application in South African higher education remains limited and underexplored, resulting in an application gap. This paper, as Phase 1 of a larger project, addresses this gap by focusing on the development of a Retrieval-Augmented Generation (RAG) web application designed to enhance Internal Auditing education at the Durban University of Technology. This is achieved by integrating three powerful Generative AI models—OpenAI GPT-4o-mini, Google Gemini-1.5-flash, and Anthropic Claude-3-haiku—into a single educational platform that will enable lecturers to manage and augment lecture materials while allowing students to access personalized, AI-generated content. This paper presents the design considerations, architecture, and integration techniques employed in the development of the RAG web application, offering insights into the potential of adaptive learning, personalized learning, and AI-driven tutoring in South Africa's educational landscape. This paper demonstrates how a RAG web application can provide the building blocks for future Generative AI applications that could enhance teaching and learning with minimal effort from lecturers and learners in the South African context.**

***Keywords*—*Adaptive learning; Anthropic Haiku; benefits; challenges; Generative AI; Google Gemini API Pro; higher education; internal auditing; OpenAI GPT-Turbo; personalized learning; RAG (Retrieval-Augmented Generation); South Africa***

## I. Introduction

This study represents Phase 1 of a broader research initiative. In Phase 1, we focus only on developing the RAG web application—integrating a database with advanced prompting strategies and Generative AI capabilities to support accounting education. Successive phases of this research, namely Phases 2 and 3, are considered for future execution as part of the continuing investigation. Phase 2 will involve piloting the application with Internal Auditing lecturers and students, where the impact of prompt formatting techniques and key model parameters—such as temperature, top_p, and max_tokens—will be examined. During this phase, feedback on the accuracy and relevance of AI-generated outputs will be collected, along with a cost-benefit analysis across OpenAI GPT-3 Turbo, Google Gemini API Pro, and Anthropic Haiku. Phase 3 will compare effectiveness metrics and provide recommendations on the most suitable and cost-effective Generative AI model for educational use.

Since the release of advanced Generative AI models like OpenAI's GPT-3 and GPT-4, Generative AI has rapidly gained prominence across various domains, including education. These AI-powered tools have the potential to revolutionize how knowledge is disseminated, particularly in complex fields such as Internal Auditing. The literature outlines that artificial intelligence (AI) models like OpenAI's GPT-3 Turbo, Google's Gemini API Pro, and Anthropic's Haiku are now being leveraged to enhance educational outcomes by providing real-time, personalized academic support. Studies have demonstrated the effectiveness of these models, with GPT-4, for example, showing superior performance over GPT-3.5 in answering complex questions from the Turkish Medical Specialization Exam, highlighting its potential in medical education [11]. Despite challenges such as the occurrence of false positives and negatives in AI detection tools, the value of Generative AI in education and research continues to be recognized [3]. This study is guided by the following research question: Can a RAG application integrating multiple Generative AI models be developed to support the teaching and learning experience in an Internal Auditing module at a South African university?

Regardless of the transformative potential of AI in higher education, its use in South Africa remains underexplored. Universities are in the early stages of integrating AI-driven solutions, which offer tailored learning experiences and can improve student outcomes. However, significant challenges persist, including the lack of digital infrastructure and insufficient training on AI technologies [8][18]. Furthermore, ethical considerations surrounding AI integration—such as data privacy, the handling of sensitive information, and inherent biases in AI models—complicate its adoption [20]. These concerns are particularly acute when public AI services are used, where the risks of data misuse and compromised privacy are heightened.

These issues become more pressing in an educational context as AI systems interact with sensitive student data, academic performance records and personalized learning pathways. Ensuring that AI systems do not compromise the confidentiality and integrity of this data is essential. Additionally, any cognitive biases embedded in AI models can affect the fairness of assessments, feedback and learning outcomes, which could exacerbate existing educational inequities. Addressing these challenges is critical to ensuring that AI systems are deployed responsibly and equitably in educational settings, safeguarding both student privacy and academic integrity [1],[6],[8],[9],[17].

Regardless of these hurdles, AI has the capacity to enhance educational content delivery, making learning more accessible and personalized. For instance, AI can support adaptive learning environments where students receive individualized instruction based on their performance, helping to bridge educational gaps [8]. Additionally, AI can automate administrative tasks such as grading and feedback, allowing educators to focus more on engaging with students and developing interactive learning experiences. These technologies have the potential to not only reduce the workload of educators but also to significantly enrich student learning through real-time access to global academic resources and dynamic, data-driven insights.

In South Africa, the challenges are compounded by the need for cost-effective and reliable AI solutions that can be scaled across diverse educational settings. This study seeks to fill the gap in research by developing a Retrieval-Augmented Generation (RAG) web application that integrates three leading Generative AI models: OpenAI GPT- Turbo, Google Gemini API Pro, and Anthropic Haiku. This application will be designed to support an Internal Auditing module at the Durban University of Technology, providing real-time, global insights on academic topics.

To address the potential risks associated with AI usage, this study also emphasizes the importance of incorporating advanced prompting techniques, such as Chain of Thought (CoT), Tree of Thought (ToT), and Rephrase and Respond (RaR). These techniques are intended to guide AI models to generate more accurate and contextually relevant outputs, thereby enhancing the reliability of the AI-generated content and ensuring academic trustworthiness.

In the next section, the current literature on Generative AI models in education is reviewed, followed by a discussion of the requirements and design considerations for the RAG web application. Subsequently, the implementation process is detailed, including the integration of advanced prompting techniques and the evaluation of the application's effectiveness. The paper concludes with a discussion of the findings, implications for higher education, and recommendations for future research.

## II. Generative AI Research

The advent of Generative AI models, particularly in educational settings, has garnered significant attention, with various studies highlighting their potential and challenges. The application of AI in education spans multiple domains, from language learning [8] to tutoring systems [6], each utilizing AI's capabilities to enhance learning outcomes. However, the deployment of AI in specialized fields like Internal Auditing is still emerging. The themes evident from the literature on AI in education discussed in this paper are AI in language learning, Generative AI in higher education and existing AI-powered platforms.

### *A. AI in Language Learning*

Existing research on AI-powered language learning platforms and chatbots demonstrates a wide range of applications [23]. One prominent application is in personalized learning systems, which utilize adaptive algorithms to cater to individual learners' needs. For example, such systems can dynamically adjust learning content based on students' performance and engagement [12]. This personalized approach has been shown to improve learning outcomes, particularly in language learning environments where learners benefit from real-time feedback and tailored support [8],[14],[19].

Validation tests for AI-driven educational platforms, such as those used in language learning, have shown significant improvements in training accuracy and reduced error rates [5]. Specifically, these reduced error rates refer to the system's ability to produce more accurate responses compared to human-provided answers. In this context, “error rates” represent the frequency of incorrect responses generated by the AI during assessments. As the system refines its models over time, adapting to the learning data, it becomes more precise, reducing the occurrence of mistakes and improving overall reliability in real-world applications [5].

### *B. Generative AI in Higher Education*

While the use of AI in language learning is well-documented, its application in higher education, particularly in specialized fields like Internal Auditing, remains underexplored. Studies have shown that Generative AI models like GPT-3 and GPT-4 significantly enrich learning by offering real-time, personalized academic support [8]. However, the adoption of such technologies in South Africa's higher education system is still in its infancy. For example, AI integration in legal education has improved student engagement, with learners achieving faster grade improvements by utilizing AI tools to tackle complex topics such as case analysis [4],[15]. Furthermore, the integration of AI in journalism education is also being explored. AI has the potential to improve productivity in news production, leading to curriculum adaptations to incorporate AI usage, ethical considerations and its applications in modern newsrooms [13].

The introduction of newer Generative AI models like OpenAI GPT-4, Google Gemini, and Anthropic Claude has expanded the potential of AI in educational environments. OpenAI GPT-4, widely recognized for its application in autodidactic learning, supports self-directed learners by providing personalized guidance, real-time feedback, and interactive assistance [7]. Anthropic Claude, with its focus on ethical AI, has shown promising results in educational applications. For example, Claude was tested alongside GPT models in creating virtual patients for medical education, offering scalable and low-cost simulations that improve clinical reasoning and decision-making skills [2]. Claude's design emphasizes transparency, ethical deployment, and minimizing harmful biases, making it a reliable tool for equitable educational environments. These attributes, alongside its role in AI governance and accountability, make Claude particularly well-suited for educational institutions prioritizing responsible AI deployment [21].

Google Gemini, a multimodal AI system, has demonstrated significant advancements in real-time processing of diverse data types such as text, images, audio, and video, making it particularly suitable for dynamic, multidisciplinary academic environments. Its unique mixture-of-experts architecture allows for highly efficient processing, enabling greater scalability and

adaptability in educational applications, especially in fields like law, science and healthcare, where handling multimodal information is crucial [16]. These capabilities position Gemini as a capable tool for providing enriched, interactive learning experiences in higher education.

### C. Existing AI-Powered Platforms

Several AI-powered platforms have been developed for language learning, such as Duolingo and Cleverbot, focusing primarily on vocabulary and grammar drills. Duolingo, which utilizes gamification and adaptive learning techniques, enables learners to manage their pace and content through structured modules but often lacks the depth needed for more specialized fields like Internal Auditing [10]. Similarly, Cleverbot, a chatbot-based platform, engages users in conversational exchanges by learning from past interactions. However, its primary strength lies in mimicking human conversation rather than offering adaptive or context-aware learning experiences that could evolve based on the user's subject matter expertise [22]. In contrast, the proposed RAG-based system in this study aims to address these limitations by offering tailored academic support for Internal Auditing, providing specialized and personalized learning paths for students at the Durban University of Technology at the directive of the lecturer and in line with the module outcomes.

This study builds on the existing body of research by exploring the application of Generative AI models in a new context, higher education in South Africa, specifically within the Internal Auditing module. By leveraging the strengths of OpenAI GPT-4-mini, Claude-3-haiku-20240307, and Google Gemini-1.5-flash, this study aims to develop a RAG web application that not only enhances learning outcomes but also addresses the unique challenges faced by educational institutions in South Africa.

## III. Research Methodology

This section details the methodology employed in the development of a RAG web application designed to enhance the learning experience for students in an Internal Auditing module at the Durban University of Technology. The methodology integrates multiple cutting-edge Generative AI models into a Python Flask web application, supported by SQLite for data management. The process follows a structured approach to ensure the application is functional, scalable, and suited to the educational context. Fig. 1 provides a visual representation of the workflow, showing the interaction between lecturers, students, AI models, and the SQL database. Lecturers create and manage lecture content, while students access both lecture content and AI-generated materials. The flow of data between the users, AI models, and the database supports dynamic and personalized learning experiences.

### A. Web Application Development with Python Flask

The web application was developed using Python Flask, a lightweight framework ideal for the pilot of our educational application that requires real-time user interaction.

*1) Authentication and user management:* The authentication system supports login, signup, and logout functionalities with role-based access control. During the signup process, users are assigned roles: lecturer or student. Lecturers use the system to manage lecture content, while students access lecturer and AI-generated materials.

*2) Lecture management:* Lecturers can create, edit, and manage lecture questions and answers through a set of web forms. This content is stored in an SQLite database, ensuring that all data is securely saved and retrievable for AI-driven content generation.

Fig. 2 illustrates the list view of the Lecture Management interface, where lecturers can view all previously created lecture questions. The list includes columns for the topic, question, answer, and focus, along with action buttons to view details, edit, or delete content. The TutorAI button allows lecturers to invoke AI to generate content based on existing questions and answers. This streamlined interface helps lecturers keep track of lecture materials and manage them efficiently.

Fig. 3 illustrates the creation form where lecturers can add new lecturer questions. The form includes fields for entering the overarching lecture topic, desired question, expected answer, and focus area (industry, local, global, etc.), allowing lecturers to define the specific content they wish to include in their lecture. Once submitted, the new question is added to the list, as seen in Fig. 2, where it can be managed further through the available actions.

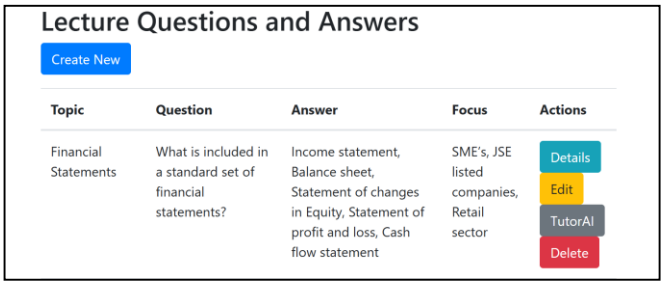


Fig. 1. Lecture management - List view (add, edit, delete questions and answers).

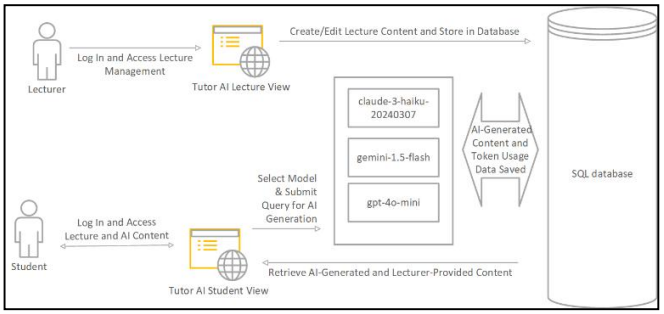


Fig. 2. Application flow.

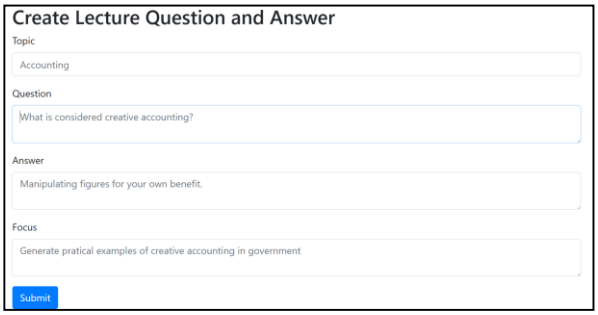


Fig. 3. Lecture management: Create lecture question and answer screen.

## B. Integration of Generative AI Models

The RAG web application integrates three Generative AI models to provide students with dynamic and personalized educational content based on the lecturer-provided lecture questions. This functionality allows students to enhance their understanding by accessing AI-generated answers and examples directly aligned with their course materials.

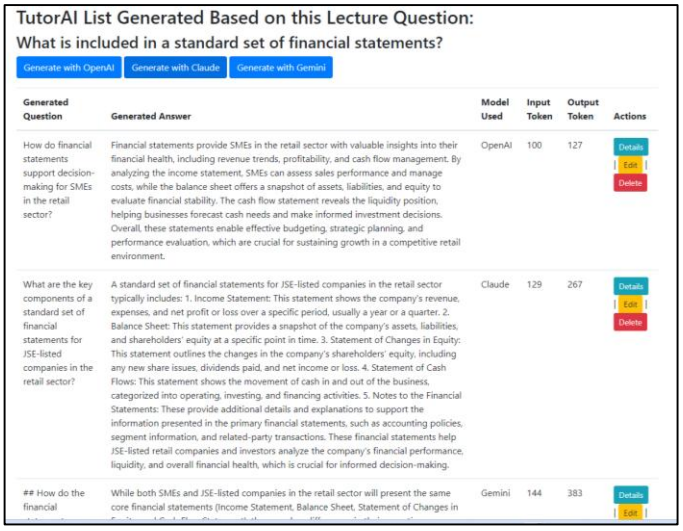


Fig. 4. TutorAI integration of Generative AI models for students.

Fig. 4 illustrates how students can interact with the TutorAI system by generating additional questions and answers related to their lecture materials. Students have the option to select from three AI models, 1) OpenAI GPT-4o-mini, 2) Anthropic Claude-3-haiku, and 3) Google Gemini-1.5-flash, based on their content needs.

*1) OpenAI GPT-4o-mini:* This model generates in-depth answers and explanations related to the lecture material. When a student clicks "Generate with OpenAI," the model processes the lecture question and returns detailed responses. The input and output tokens (reflecting the number of tokens used for generating content) are tracked to monitor how much content is generated for each query.

*2) Anthropic Claude-3-haiku-20240307:* Students can select this model for more creative and comprehensive explanations. By choosing "Generate with Claude," students receive answers that delve into broader interpretations or applications of their lecture content, which helps deepen their understanding.

*3) Google Gemini-1.5-flash:* This model is ideal for concise, fact-based content. When students click "Generate with Gemini," they get brief, straightforward answers, which are useful for summarizing or revisiting key lecture concepts. Token usage data is also tracked here.

The generated content is displayed in a structured table, which includes the question, the AI-generated answer, the model used, and token usage statistics. Students can also view more details and edit or delete the generated content, providing them with flexibility in managing the information they receive.

By offering these AI models, the system empowers students to explore multiple perspectives and explanations on lecture topics, enhancing their learning experience through AI-generated content that is tailored to their academic needs.

## C. Data Management with SQLite

SQLite is used for data storage, providing a secure and scalable solution for managing user data, lecture materials, and AI-generated content. Data management for this study is discussed under database configuration, data security, and token usage tracking.

*1) Database configuration:* The SQLite database serves as the primary repository for lecture content, user data, and AI-generated responses. A structured database schema ensures easy retrieval of data for both lecturers and students.

*2) Data security:* The application employs secure connection strings to SQLite, with strict role-based access control to protect sensitive data.

*3) Token usage tracking:* In order to manage the costs of using external AI APIs, the system tracks token usage (input and output) for each AI model. This data is stored in the database to monitor efficiency and manage costs.

## D. Workflow and System Architecture

The architecture supports seamless interaction between users, AI models, and the database. User interaction, AI content generation, and response delivery are considered at this stage.

*1) User interaction:* Lecturers and students interact with the system through web interfaces: Lecturers manage lecture content and students access AI-generated content. These interfaces are user-friendly and responsive.

*2) AI Content generation:* When a user submits a query, the system constructs a prompt using stored lecture data and sends it to the selected AI model. The AI model generates content, which is stored in the database for future access.

*3) Response delivery:* The generated content is then delivered to the user in a formatted and accessible manner, providing real-time feedback and enhancing the learning experience.

## E. Implementation Challenges and Solutions

Several challenges were encountered during development and are summarized under model integration, data privacy, scalability and cost management.

*1) Model integration:* Managing multiple AI models requires careful handling of API keys and response formats. Standardized prompts and consistent response parsing were implemented to ensure coherence across models.

*2) Data privacy:* Protecting user data was a top priority. The system uses encrypted connections to SQLite and strict access control to safeguard sensitive information.

*3) Scalability and cost management:* By tracking token usage across the AI models, the system monitors API efficiency and manages costs, ensuring scalability as user activity grows.

## IV. Findings and Implications for Higher Education

The development of the RAG web application demonstrates the successful integration of multiple Generative AI models to enhance the educational experience for students in an Internal Auditing module at the Durban University of Technology. By leveraging cutting-edge AI models, OpenAI GPT-4o-mini, Google Gemini-1.5-flash, and Anthropic Claude-3-haiku, the application provides dynamic, personalized content to support both lecturers and students.

Lecturers can efficiently manage their lecture materials, create and update content, and utilize AI-generated enhancements to enrich their teaching. Meanwhile, students are empowered with tailored AI-generated responses, offering multiple perspectives and deeper insights into the course material. The system architecture, built on Python Flask and supported by Azure SQL, ensures that the platform is scalable, secure, and cost-effective, addressing the specific needs of the academic environment.

The integration of role-based access control, seamless data management, and AI-driven content generation allows for an interactive and flexible learning experience. As AI technologies continue to evolve, this application sets the stage for further innovations in educational tools, offering a model for how institutions can harness the power of AI to improve academic outcomes.

## V. Conclusion

The RAG web application not only integrates multiple Generative AI models to support the teaching and learning experience but also provides a blueprint for future applications of AI in higher education, transforming traditional learning methods into more interactive and personalized experiences. Higher education institutions can leverage the RAG web application to drive and support more effective and real-world student solutions.

Although the development of the RAG shows promise, the accuracy and relevance of the Generative AI outputs necessitate further research to be performed on the implementation of the application. As Phase 2 of a broader research initiative, this needs to be done through a pilot study. During this phase, feedback on the accuracy and relevance of AI-generated outputs will be collected, along with a cost-benefit analysis across OpenAI GPT-3 Turbo, Google Gemini API Pro, and Anthropic Haiku.

Given the use of AI applications and the associated costs, a cost-benefit analysis must be carried out. Phase 3 of a broader research initiative will entail the comparison of costs, relevance and accuracy associated with OpenAI GPT-3 Turbo, Google Gemini API Pro, and Anthropic Haiku. The most cost-effective and accurate Generative AI model for educational purposes among the three AI platforms will need to be determined. This will entail the analysis of the feedback and cost data collected. Researchers and developers can warrant the responsible, positive and cost-effective disposition of a RAG web application in various disciplines at a higher education setting while shielding against likely risks.

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# Development of an Interactive Oral English Translation System Leveraging Deep Learning Techniques

Dan Zhao[1], HeXu Yang[2*]
School of Foreign Studies, Ningxia Institute of Science and Technology, Shi Zuishan 753000, China[1]
School of Mechanical Engineering, Ningxia Institute of Science and Technology, Shi Zuishan 753000, China[2]

***Abstract*—An advanced interactive English oral automatic translation system has been developed using cutting-edge deep learning techniques to address key challenges such as low success rates, lengthy processing times, and limited accuracy in current systems. The core of this innovation lies in a sophisticated deep learning translation model that leverages neural network architectures, combining logarithmic and linear models to efficiently map and decompose the activation functions of target neurons. The system dynamically calculates neuron weight ratios and compares vector levels, enabling precise and responsive interactive translations. A robust system framework is established around a central text conversion module, integrating hardware components such as the I/O bus, I/O bridge, recorder, interactive information collector, and an initial language correction unit. Key hardware includes the WT588F02 recording and playback chip (with external flash) for audio recording and NAND flash memory for efficient data storage. Noise reduction is achieved using the POROSVOC-PNC201 audio processor, while the aml100 chip enhances audio detection capabilities. The extensive neuron network testing using a dataset of 1.8 million translation samples demonstrates the system's superior performance, achieving an impressive success rate exceeding 80%, a rapid translation time of under 50ms, and a remarkable translation accuracy of over 95%. This state-of-the-art system sets a new benchmark in interactive English oral translation, achieving a success rate exceeding 80% (a 10% improvement over existing methods), a rapid translation time of under 50ms (a 30% reduction), and a remarkable translation accuracy of over 95% (a 5% improvement), by combining deep learning advancements with high-performance computing and optimized hardware integration.**

***Keywords*—Deep learning; interactive English; spoken English; automatic translation; translation system**

## I. Introduction

Artificial intelligence big models are "large parameter" models trained using large-scale data and powerful computing power. With their high versatility and generalization capabilities, these models have shown extraordinary potential in many fields such as natural language processing, image recognition, and speech recognition. Artificial intelligence big models can be subdivided into big language models, big visual models, multimodal big models, and basic big models, which are constantly promoting technological innovation and progress in their respective fields.

Computer science is a practical technical discipline that systematically studies the theoretical basis of information and computing and how these theories can be implemented and applied in computer systems. Computer science not only covers systematic research on algorithmic processing for creating, describing, and transforming information, but also includes many branches. From computer graphics that emphasizes the calculation of specific results, to computational complexity theory that explores the nature of computational problems, to programming language theory and program design that focus on realizing calculations, and human-computer interaction that is committed to improving the usefulness and usability of computers and computing, computer science provides a solid theoretical foundation and rich technical means for the development of artificial intelligence.

Oral translation, as a type of instantaneous interactive learning, has high requirements for the accuracy and adaptability of translation systems. Regarding the issue of interactive English oral translation, scholars in related fields have conducted in-depth research. For example, in [1] proposes an interactive oral machine translation system based on semantic analysis, which uses semantic analysis technology to convert source speech into text and improve translation quality by analyzing language texts. However, this system requires extremely high logical compilation and has poor translation accuracy. In [2], designed a bidirectional English online auxiliary translation system based on human-computer interaction, which displays translation results based on the similarity between words analyzed by a corpus. This system can evenly distribute the frequency of markers, but its dependence on the corpus is too high, resulting in a low success rate of translation. In [3], designed an automatic calibration system for English spoken pronunciation based on speech perception technology, which achieves high accuracy in correcting English spoken pronunciation but has a long calibration process and poor instantaneous translation ability. In contrast, our proposed system leverages advanced deep learning techniques to address these limitations.

Deep learning technology, as a type of machine learning, combines grassroots features to obtain a more abstract high-level representation of attribute categories or features, thereby more clearly discovering distributed features of data. It has strong analytical capabilities for both sound and text. Deep learning technology can achieve information learning by establishing an appropriate number of neural computing nodes and a multi-layer computational hierarchy and further optimizing the data characteristics to detect text data features. After detecting the functional relationship between input and

*Corresponding Author.

output, the correlation between texts is determined to achieve information exchange. Therefore, this article designs a new interactive English oral automatic translation system based on deep learning algorithms, optimizes the system hardware and software, uses deep learning technology to transform features layer by layer, enriches the internal information of the data based on learning features, and tests the actual application effect of the interactive English oral automatic translation system designed in this article through experiments. Therefore, this article designs a new interactive English oral automatic translation system based on deep learning algorithms. The objectives of this study are to propose an efficient and accurate translation system, optimize its hardware and software components, and evaluate its performance through experiments. The rest of this study is organized as follows: Section II describes the framework design of the proposed system, Section III details the hardware design, Section IV presents the software design, Section V reports the experimental study, Section VI presents results, and Section VII concludes the study.

## II. Framework Design of Interactive Oral English Automatic Translation System Based on Deep Learning

### A. Principles of Deep Learning

The interactive spoken English is automatically translated using deep learning technology. The translation model is shown in Fig. 1:

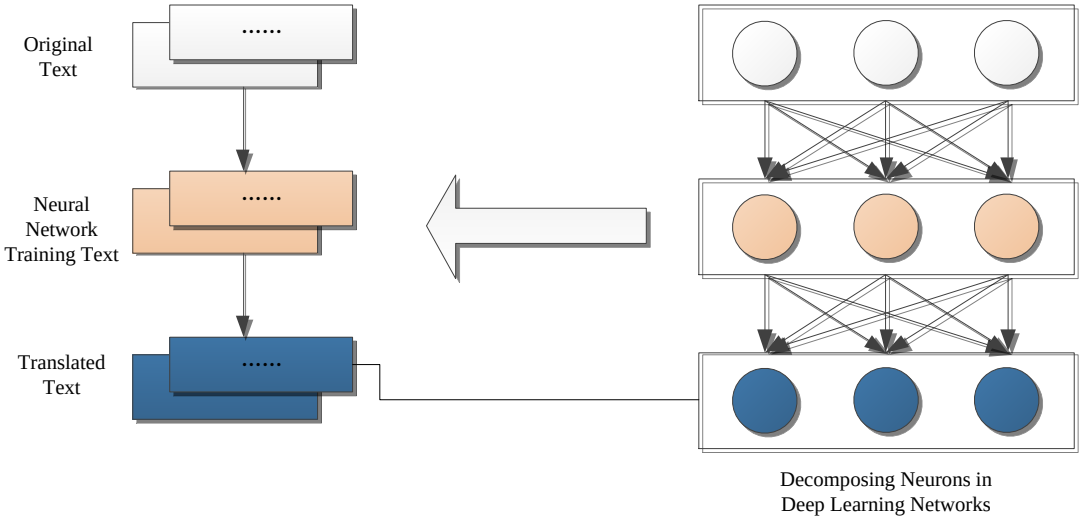



Fig. 1. Deep Learning translation model.

Set $x$ as input information text and $y$ as output text, $\theta$ as a conversion function, a linear model of input information text is established according to the characteristics of language structure, as shown in Formula (1):

$$P(y|\ x;\theta)=\sum_{z}\frac{\exp(\theta\cdot\phi(x,y,z))}{\sum_{y'}\sum_{z'}\exp\left(\theta\cdot\phi\left(x,y',z'\right)\right)} \tag{1}$$

wherein, $P(y|\ x;\theta)$ is the obtained logarithmic linear model mapping, the implicit language structure phrase is set as the basic translation unit, and the input text information is set as the target neuron. The activation function of the target neuron is decomposed in the relevant neurons of the neural network. The decomposition process is as follows:

$$f_m=\sum_{u\in C(f_m)}\sum_{n=1}^{N}r_{u_n\leftarrow f_m} \tag{2}$$

$$f_1=\sum_{n=1}^{3}r_{u_n\leftarrow f_1} \tag{3}$$

wherein, $f_m$ is the target neuron to be decomposed; $C(f_m)$ is the collection of neurons; $N$ is the number of neurons; $r_{u_n\leftarrow f_m}$ is the corresponding relationship; $f_1$ is the data value after decomposition.

After decomposing the activation function value, the neuron level correlation is calculated. The calculation method selected in this study is a backward propagation recursive algorithm. The calculation process is as follows:

$$r_{u\leftarrow f}=\sum_{o\in \mathrm{OUT}(u)}w_{u\to o}r_{o\leftarrow v} \tag{4}$$

wherein, $r_{u\leftarrow f}$ is the neuron-related data after recursion; $o$ represents the target neuron selected in the recurrent neural network.

While using backward propagation recursively to calculate neuron level correlation, the weight ratio of current neurons is calculated through forward propagation as follows:

$$w_{u\to f}=\frac{\mathbf{W}_{u,f}u}{\sum_{u'\in \mathrm{IN}(f)}\mathbf{W}_{u',f}u'} \tag{5}$$

The data are labeled according to the weight ratio to obtain small-scale labeled data. Other data are large-scale unlabeled data. The semi-supervised learning is completed by using the deep learning network. The calculation process is as follows:

$$J(\vec{\theta},\overleftarrow{\theta})=\sum_{n=1}^{N}\log P\left(y^{(n)}|\ x^{(n)};\vec{\theta}\right)+\sum_{n=1}^{N}\log P\left(x^{(n)}|\ y^{(n)};\overleftarrow{\theta}\right)$$
$$+\tau_1\sum_{t=1}^{T}\log P\left(y^{'}|\ y^{(t)};\vec{\theta},\overleftarrow{\theta}\right)+\tau_2\sum_{s=1}^{S}\log P\left(x^{'}|\ x^{(s)};\vec{\theta},\overleftarrow{\theta}\right) \quad (6)$$

Among them, $\sum_{n=1}^{N}\log P\left(y^{(n)}|\ x^{(n)};\vec{\theta}\right)$ indicates the possibility of translating the original text into the target text, and the translation mode is forward translation; $\sum_{n=1}^{N}\log P\left(x^{(n)}|\ y^{(n)};\overleftarrow{\theta}\right)$ indicates the possibility of translating the target text into the original text, and the translation mode is backward translation [4-5]; $\tau_1\sum_{t=1}^{T}\log P\left(y^{'}|\ y^{(t)};\vec{\theta},\overleftarrow{\theta}\right)$ is the original text neural network; $\tau_2\sum_{s=1}^{S}\log P\left(x^{'}|\ x^{(s)};\vec{\theta},\overleftarrow{\theta}\right)$ is the target text neural network.

The translation content is determined by comparing the vector-level relevance to achieve Interactive Oral English Translation. The mathematical model of translation is as follows:

$$R_{u\leftarrow f}=\sum_{m=1}^{M}\sum_{n=1}^{N}r_{u_n\leftarrow v_f} \quad (7)$$

Formula (7) represents the translation result [6].

### B. Frame Structure Design

The automatic translation system of spoken English designed in this study has strong interactive ability. After obtaining the real-time voice, it can convert the voice into text. The correction module is set inside the system, which can well ensure the accuracy of spoken English translation. The framework of the translation system is shown in Fig. 2:

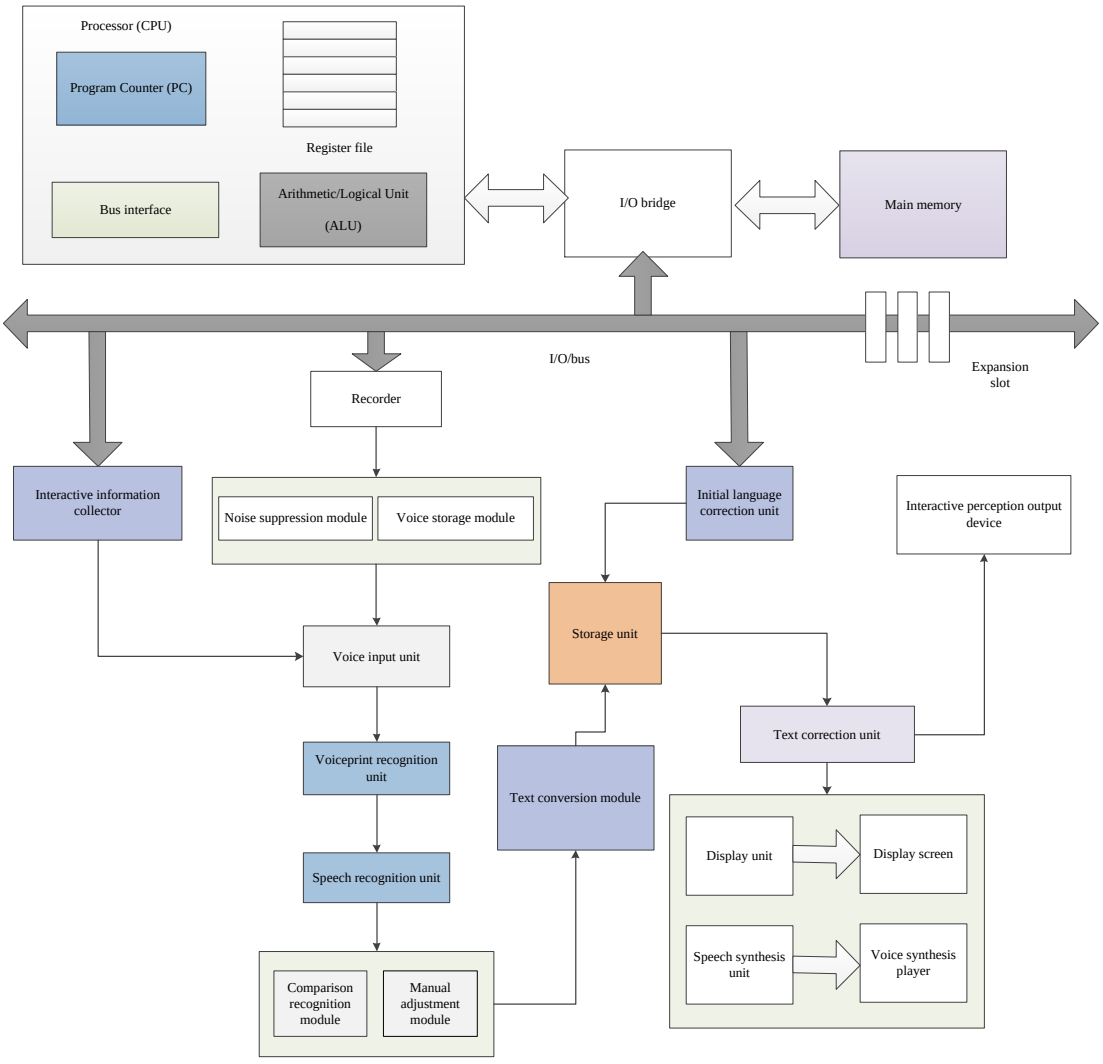



Fig. 2. Framework of translation system.

According to the Fig. 2, the internal bus of the translation system framework in this study connects the I/O bridge, recorder, interactive information collector, and initial language correction unit. The bus word length is 8 bytes (64 bits), and the bus is responsible for information interaction. The central processing unit (CPU) inside the system is mainly responsible for sending, interpreting, or executing the instructions inside the system. The program counter (PC) is the core device of the CPU, with a size of 1 byte. During the operation of the system, the PC always points to various machine language instructions. When

the CPU receives the instructions, it will continuously update the program counter to execute the instructions of the processor. After completing an instruction, the PC will point to the next instruction. The CPU will then carry out new work. The working process of the processor mainly includes loading, operation, storage, and jump. The specific execution process is as follows: after receiving the translation command, the system will automatically collect the target text, copy a byte of the target text from the main memory to the register, and use the copied content to replace the original content of the register. When the two-word contents of the two registers are copied to the arithmetic logic unit (ALU), the ALU will perform operations on the two words copied and store the operation result in the original register to complete the operation. After the register runs for a period of time, it will copy an internal byte or a word to a location in the main memory. Through this operation, the content in the original location of the main memory will be overwritten to complete the storage. After the storage is realized, the CPU needs to start a new instruction, extract a word from the original instruction [7]-[8], and copy the extracted content to the PC. After overwriting the original value of the PC, start a new command.

The I/O bus is connected to the interactive information collector and recorder at the same time. The voice information to be converted is collected through the above equipment. The collected information will be transmitted to the voice input unit at the same time. The in-depth detection of voice will be carried out through the double recognition of voiceprint recognition and voice recognition. Under the work of the comparison recognition module and the adjustment module, the transferred information will be automatically converted. After the converted text and the corrected information of the initial language enter the storage unit, the correction is implemented in the text correction unit, the translation results are displayed by the display and voice synthesis player, and the output content is backed up in the interactive perception output device.

## III. Hardware Design of an Interactive Oral English Automatic Translation System Based on Deep Learning

An automatic translation system is established under the deep learning network. The hardware structure of the system (Fig. 3) is as follows:

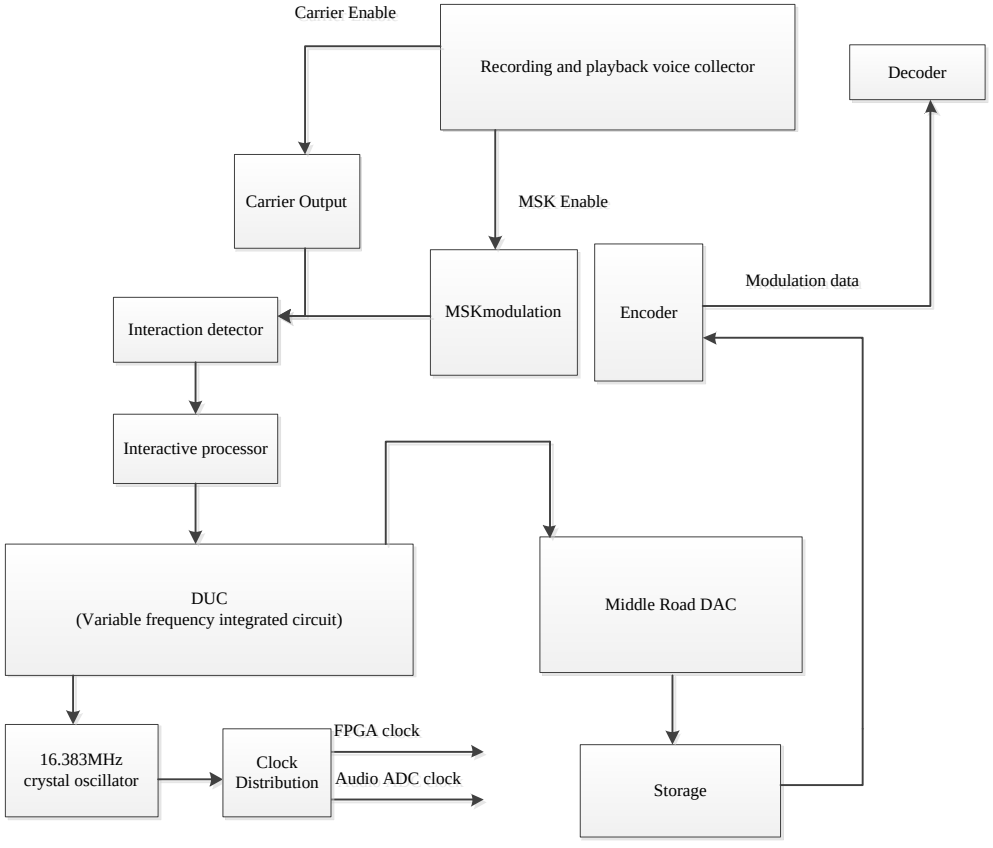



Fig. 3. Hardware structure of automatic translation system.

It can be seen from Fig. 3 that the collector outputs signal through carrier enable and MSK enable and performs carrier output processing and MSK modulation processing, respectively. The processed text data successively enters the interaction detector and interaction processor. The frequency conversion integrated circuit and crystal oscillator are used to complete clock distribution. The allocated data enters the memory and is modulated by the encoder. In the process of translation, when the encoder is in a working state, the decoder must keep waiting until all the encoders have finished their work. The decoder uses the parallel technology of a deep neural network to realize translation and output the final translation results.

### A. Recording and Playing Voice Chip

The audio recording and playback chip selected in this study is the Wt588f02 audio recording and playback (external flash) chip. The working voltage of the chip is 2.0 to 5.5V. The internal low-voltage reset (lvr=1.8v) watchdog has a strong timing function. Even if there is a vibration inside, it will float at +/-1%. It is controlled by a serial port and can sample 16KHz recording at most. The built-in 2M bit flash of the chip has a self-healing function. The main program data and flash data in the voice chip can be erased and then burned [9]. The chip and pin are shown in Fig. 4.

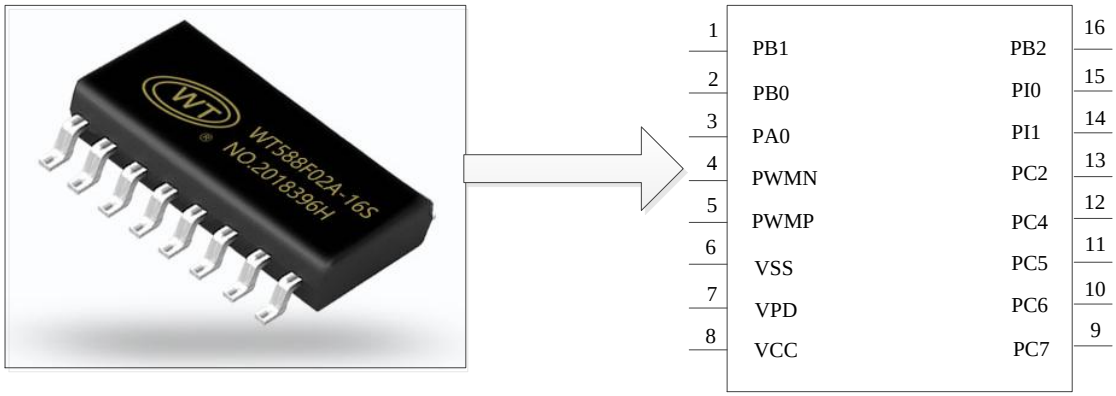



Fig. 4. Wt588f02 recording and playback chip and pin.

The Pin description is shown in Table I:

TABLE I. PIN DESCRIPTION

| Name | Serial number | Attribute | Describe |
|---|---|---|---|
| PB1 | 1 | I/O | SPI communication pin |
| Pb0 | 2 | I/O | SPI communication pin |
| PA0 | 3 | I/O | Data |
| Pwmn | 4 | Out | Horn port |
| Pwmp | 5 | Out | Horn port |
| VSS | 6 | Power | GND |
| VPD | 7 | Power | Internal power supply and discharge |
| VCC | 8 | Power | Power supply positive pole |
| PC7 | 9 | I/O | Mic interface terminal (refer to the reference circuit for connection) |
| PC6 | 10 | I/O | Mic interface terminal (refer to the reference circuit for connection) |
| PC5 | 11 | I/O | Mic interface terminal (refer to the reference circuit for connection) |
| PC4 | 12 | I/O | —— |
| PC2 | 13 | NC | —— |
| PC1 | 14 | I/O | SPI communication pin |
| P10 | 15 | I/O | Busy |
| PB2 | 16 | NC | SPI communication pin |

### B. Memory

The memory selected in this study is NAND flash memory, and the memory structure is shown in Fig. 5.

As a kind of flash memory, NAND flash memory uses a nonlinear macro cell mode internally, with a maximum bandwidth of 100GB per second. The internal cell density is extremely high, which can ensure the storage of a large number of voice text information, ensure the storage density, and effectively improve the writing and erasing speed. Since the input translated text data is saved in array mode, after consolidation and management, the storage array runs in a pool, which can reduce the amount of calculation during operation, and the response time is less than 50 μ s. The processor inside the memory is Intel Ice Lake, and the maximum port of the front-end host is 48. The prediction and analysis technology inside the memory can monitor the storage state well and [10], optimize the storage state at any time so as to ensure storage efficiency.

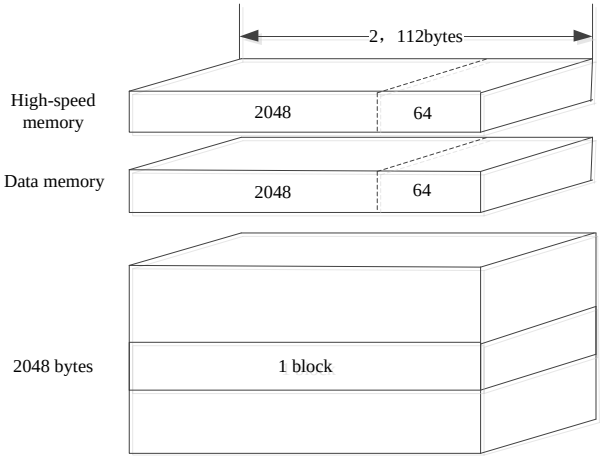



Fig. 5. NAND flash memory structure.

### C. Audio Processor

The audio processor selected in this study is the POROSVOC-PNC201 audio processor. The processor uses the DNN neural network noise reduction algorithm, deep neural network echo cancellation algorithm, AGC automatic gain adjustment algorithm, howl suppression, reverberation elimination and other technologies, AI algorithm+embedded SOC chip deep fusion technology. Under the deep learning technology, it completes sample training, eliminates various noises in the external environment, and realizes blind source separation, ensuring that the input sound source is valid information. The processor has a professional DSP instruction

set, which can process signals well. The FPU operation unit enables the processor to support floating-point operation and cooperate with the FFT accelerator to ensure the processing speed.

### D. Audio Detector

The audio detection chip selected in this study is the aml100 chip, which uses digital analog technology to complete machine learning and data calculation to ensure that the data calculation results are closer to the data source. The chip is composed of a group of independent configurable analog modules, which can support various audio detection functions through software programming technology. Compared with the traditional single mode, the aml100 chip is more flexible. Using 7mm x 7mm 48-pin QFN package, it can effectively reduce power consumption and ensure that the power consumption operation process is less than 20 μ A. The field programmable function enables the chip to meet the requirements of different occasions.

## IV. Software Design of Interactive Oral English Automatic Translation System Based on Deep Learning

After completing the hardware design, the interactive spoken English automatic translation system software is designed by using the deep learning algorithm. In the process of translation, the gradient of deep learning neural network will gradually disappear with the deepening of time dimension. Therefore, the translation system software designed in this study introduces the attention mechanism, uses the attention mechanism to identify the original information characteristics of spoken English, uses the encoder to obtain the data correlation, and obtains the probability distribution state according to the correlation analysis results. The gradient disappearance problem is solved through the residual network, by default, one layer of neural network calculates an identity function to calculate the performance of different weights at different levels when expressing the identity function. The calculation process is as follows:

$$\begin{gathered} d_1 = f_1(x) + x \\ d_2 = f_2(d_1) + h_1 = f_2 d(h_1) + f_1(x) + x \\ d_3 = f_3(d_2) + d_2 = f_3(d_2) + f_2(d_1) + d_1 = f_3(d_2) + f_2(d_1) + f_1(x) + x \\ d_n = x + \delta_1 + \delta_2 + \cdots + \delta_n \end{gathered} \tag{8}$$

where, $\chi$ is the input information; $f_1$ is the identity function of the first layer neural network; $d_1$ is the output result of the first layer neural network. By analogy, when the neural network is a $\eta$ layer [11]-[13], the output result is the neural network output data and of each layer.

The software workflow of Interactive Oral English automatic translation system based on deep learning neural network parallel algorithm and residual network is shown in Fig. 6.

### A. Sound Acquisition Model

Using deep learning algorithms to recognize interactive oral information, establish a sound acquisition model, input the collected acoustic features into the neural network in image mode, set the size of the acoustic feature map $g$ to $a \cdot b$, and process the input acoustic feature map $g$ through an excitation function. The output results of the acquisition model are as follows:

$$F_{a,b} = f\left( \sum_{m=0}^{k=1} \sum_{n=0}^{k=1} =1\left( \kappa_{m,n} g_{a+m,b+n} \right) + \kappa_e \right) \tag{9}$$

Among them, $F_{a,b}$ represents the position of the output neuron in the feature map, which is row $a$ and column $b$; $k$ represents the number of layers in the neural network; $\kappa_{m,n}$ represents the weight values of row $m$ and column $\eta$, and the weight values of the acoustic acquisition model are calculated using unsupervised and training methods; $\kappa_e$ represents the deviation value generated during the training process.

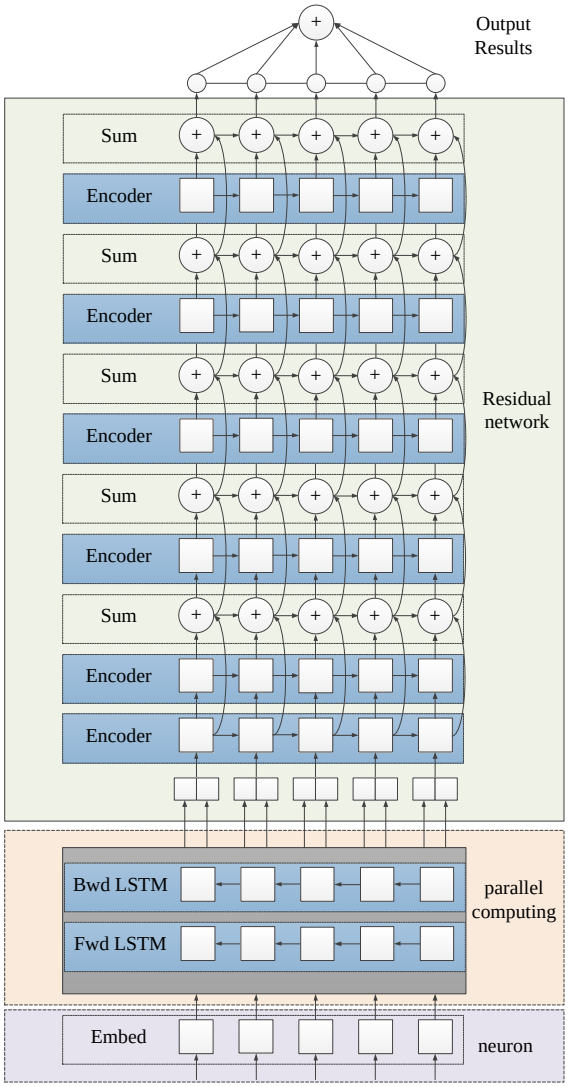



Fig. 6. Software workflow of Interactive Oral English automatic translation system.

After the output results are obtained, the backpropagation technology is used to realize the training. The neural network will produce losses in the interaction process, and each node will have errors, so the loss amount needs to be calculated. Set the node to $i$ ,the loss amount is:

$$\delta_i = -O_i\left(I_i - O_i\right)\left(1 - O_i\right) \tag{10}$$

where, $\delta_i$ represents the calculated loss result; $O_i$ represents the weighted output value; $I_i$ represents the weighted input value.

Analyze the gradient of $\kappa_{m,n}$ and complete weight iteration using gradient descent technique. The calculation process is as follows:

$$\kappa_{m,n}{}' = \kappa_{m,n} - \eta \frac{\delta}{\partial \kappa_{m,n}} \tag{11}$$

where, $\kappa_{m,n}{}'$ is the weight value after iterative update; $\eta$ represents the learning rate of the neural network; $\partial$ represents the offset value.

The acoustic acquisition model is trained through the above calculation to improve the robustness of the model [14]-[16].

### B. Feature Recognition Based on Deep Learning

Feature recognition is realized through the attention mechanism of deep learning neural network. The recognition process is shown in Fig. 7:

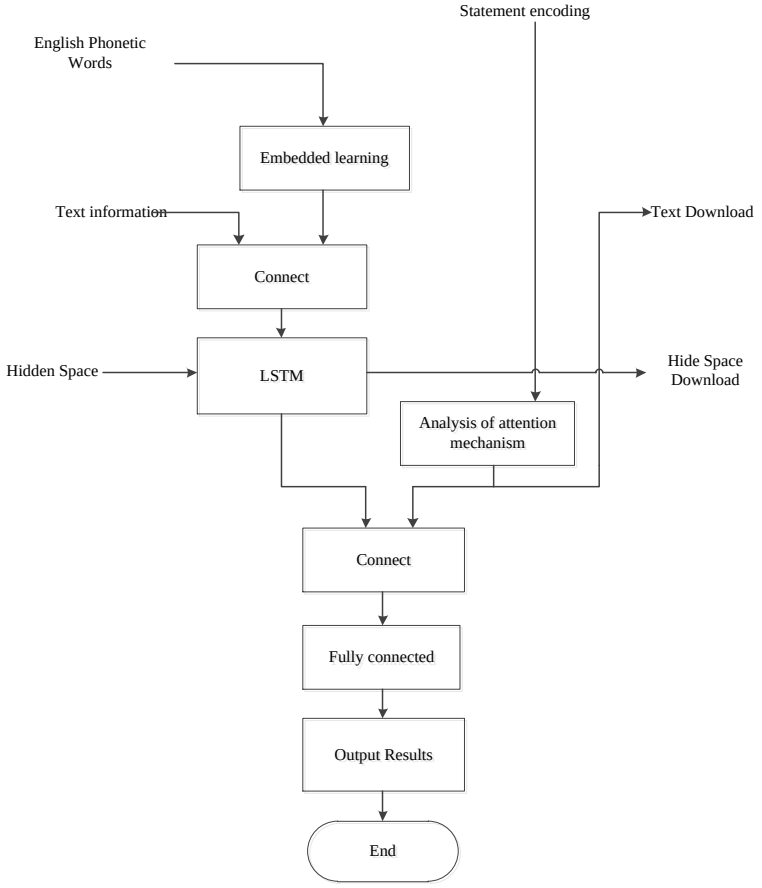



Fig. 7. Feature recognition process based on deep learning.

Select the training sample in the sound acquisition model, set the trained sample as $\wp$ , the position coordinate in the neural network as $X_\wp(x_{\wp 1}, x_{\wp 2}, \cdots x_{\wp n})$ , the learning frequency in the training process as $V_\wp(v_{\wp 1}, v_{\wp 2}, \cdots v_{\wp d})$ , the best training position of $\wp$ as $P_\wp$ , the best training of all learning particles in the training sample as $P$ , and iterate the learning particles in the deep learning space. The iterative results are as follows:

$$v_{\wp d}^{k+1} = v_{\wp d}^{k} + c_1 R\left(P_\wp^k - x_{\wp d}^k\right) + c_2 R\left(P^k - x_{\wp d}^k\right) \tag{12}$$

$$x_{\wp d}^{k+1} = x_{\wp d}^{k} + v_{\wp d}^{k+1} \tag{13}$$

where, $c_1$ represents the training depth coefficient of the optimal training position $P_\wp$ $c_2$ represents the training depth coefficient of the optimal training position $P$ . When learning particles need to consider semantic features, it is necessary to focus on the deep learning coefficient and control the training

intensity through the deep learning coefficient; $R$ represents the dynamic coefficient generated during the training process [17], and the range is (0,1).

After repeated training, the learning particle will reach the maximum training frequency $V_{\max}$ . When this value is reached, the frequency of the subsequent training process will remain constant. The depth threshold is obtained by analyzing semantic features, and the optimal solution obtained by attention detection is $S$. The result is semantic features [18].

### C. Interactive Processing of Translation Information

The obtained optimal solution $S$ is expressed through probability distribution. If the label sequence is set to $l$, the probability distribution is expressed as $p(l|\ s)$ . Translation information features are input into the neural network model to calculate the output sequence with the highest probability,

$$R(s) = \arg\max\ p(l|\ s) \tag{14}$$

optimizing maximum output sequence $R(s)$ using decoder. When predicting the information of each frame, the blank tag is inserted, and the path that can be consistent with the tag sequence is added. The noise in the sound is eliminated by the sequence, and the information is filtered. The processing result is obtained through bidirectional coding. The filtering process is as follows:

$$\ell_s = \vec{\ell}_s \oplus \overleftarrow{\ell}_s \tag{15}$$

$$\vec{\ell}_s = f\left(\vec{\ell}_{s-1}, e_s\right) \tag{16}$$

$$\overleftarrow{\ell}_s = f\left(\overleftarrow{\ell}_{s-1}, e_s\right) \tag{17}$$

wherein, $\ell_s$ represents the result of joint processing of forward encoding $\vec{\ell}_s$ and reverse encoding $\overleftarrow{\ell}_s$; $\overleftarrow{\ell}_s$ represents the activation function of neural network; $e_s$ indicates hidden status.

Delete the useless information in the voice information through interactive processing, record the standard vector after summarizing the remaining information, use the decoder to decode the data [19]-[20], and output the information iteratively after matching with the context. The interactive processing flow of translation information is shown in Fig. 8:

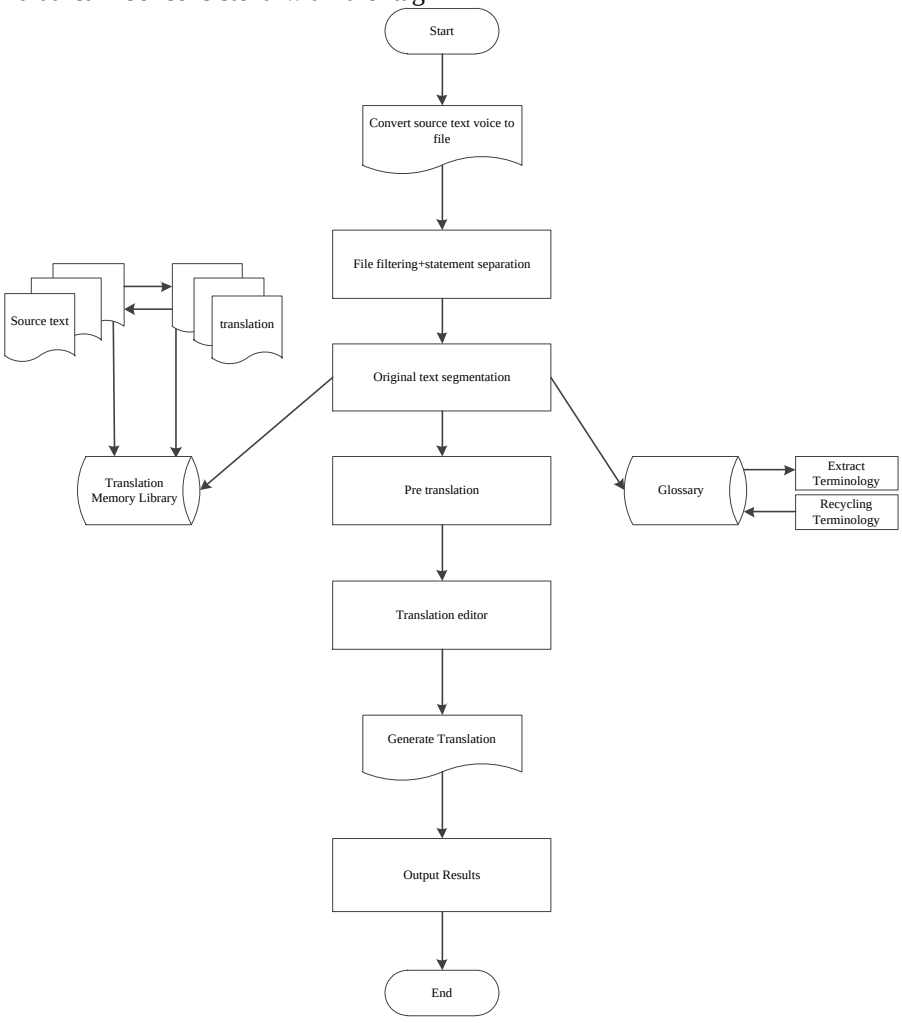



Fig. 8. Interactive processing flow of translation information.

## V. Experimental Study

In order to verify the practical application effect of the Interactive Oral English automatic translation system based on deep learning designed in this study, a comparative experiment was set. A total of 1.8 million sentences were set to be translated, including 600000 spoken words, 600000 spoken short sentences, and 600000 spoken long sentences. The system was compared with a semantic analysis translation system, human-computer interaction translation system, and language perception translation system. The translation time and translation accuracy were studied in depth. The detection time was 24hours, and the detection results were recorded every 10 minutes.

The experimental results of the translation success rate are shown in Fig. 9:

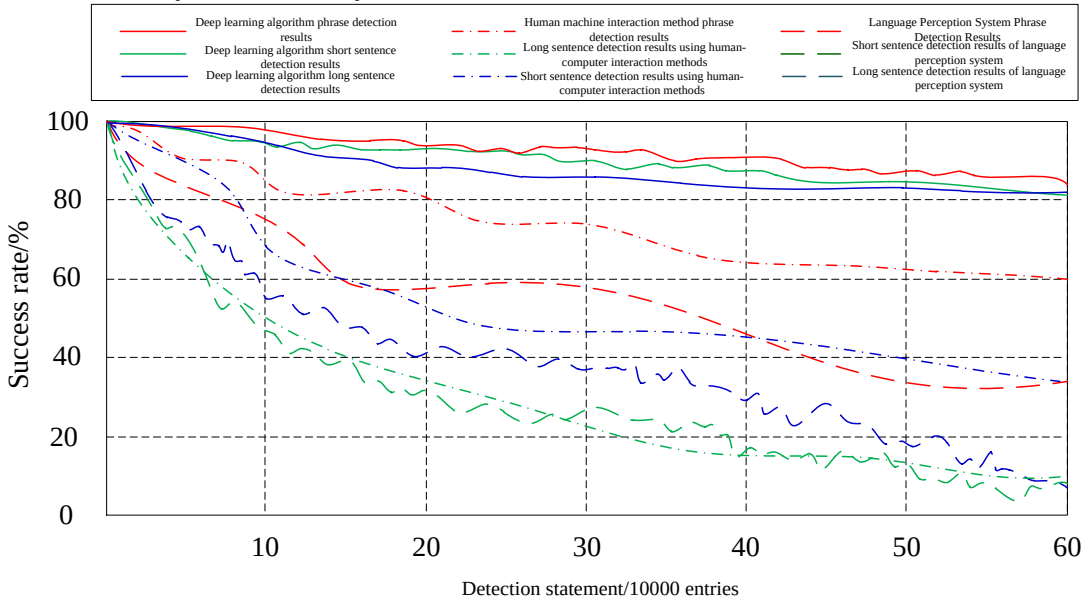
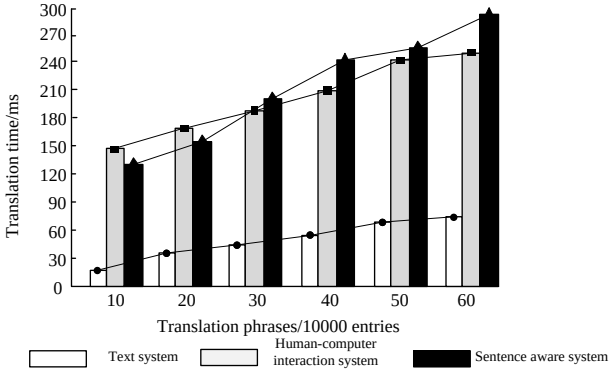



Fig. 9. Experimental results of translation success rate.

According to the above Fig. 9, as the number of detected entries/sentences increases, the success rate of translation also decreases. The three methods have the highest success rate of phrase translation and the lowest success rate of long sentences. In the process of translation, the deep learning algorithm adjusts the weights through neural network training to ensure that the output results can achieve the expected results. Therefore, the success rate of the Interactive Oral English automatic translation system based on deep learning for detecting entries/sentences is always above 80%, which is always higher than the traditional human-computer interactive translation system and language-aware translation system.

The experimental results of translation time are shown in the following Fig. 10:



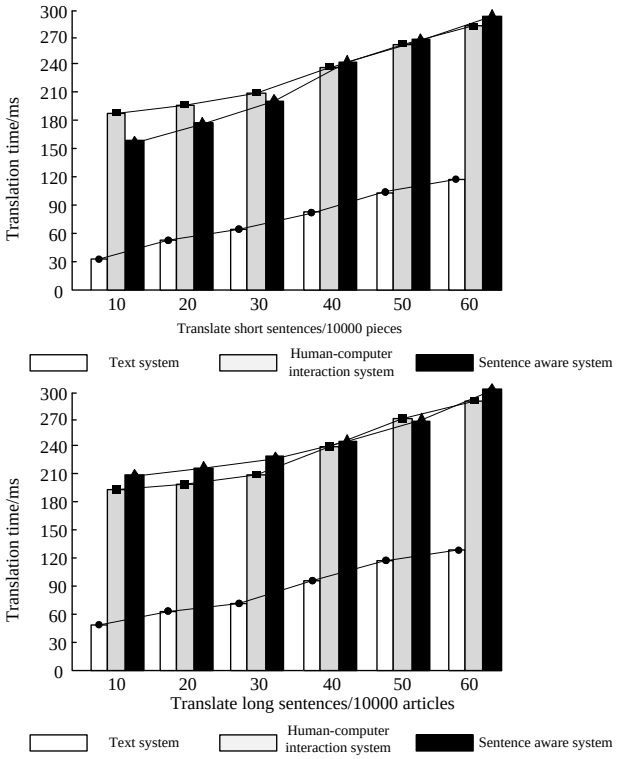




Fig. 10. Translation time experimental results.

It can be seen from the above Fig. 10 that in terms of translating phrases, short sentences and long sentences, the translation process time of the translation system proposed in this study is far less than that of the traditional translation system. When the number of translated phrases is 600000, the translation system time proposed in this study is 50ms, when the number of translated short sentences is 600000, the translation system time proposed in this study is 90ms, and when the number of translated long sentences is 600000, the translation system time proposed in this study is 105ms. It can be translated in a short time to meet the requirements of instant translation.

The experimental results of translation accuracy are shown in Table II:

TABLE II. EXPERIMENTAL RESULTS OF TRANSLATION ACCURACY

| | Number of translations/10000 | Phrase accuracy/% | Accuracy rate of short sentences/10000 | Accuracy of long sentences/% |
|---|---|---|---|---|
| Text system | 0-20 | 98.21 | 97.43 | 96.23 |
| | 20-40 | 96.44 | 96.81 | 95.67 |
| | 40-60 | 95.93 | 95.32 | 95.24 |
| Human-computer interaction system | 0-20 | 94.66 | 92.18 | 91.98 |
| | 20-40 | 91.09 | 86.64 | 88.76 |
| | 40-60 | 89.34 | 81.93 | 86.32 |
| Sentence aware system | 0-20 | 93.67 | 91.04 | 89.74 |
| | 20-40 | 90.25 | 87.29 | 85.64 |
| | 40`60 | 88.44 | 83.45 | 80.98 |

According to the above table, the translation accuracy of the translation system proposed in this study is always above 95%. Through the deep learning algorithm for oral interaction, data mining and phrase training are used to better detect the meaning of phrases and sentences so as to achieve accurate translation.

## VI. RESULTS

The extensive neuron network testing using a dataset of 1.8 million translation samples demonstrates the superior performance of the proposed system. The key results are as follows:

*1) Translation success rate:* The system achieves a success rate exceeding 80%, significantly higher than traditional translation systems.

*2) Translation time:* The translation time is under 50ms for phrases, 90ms for short sentences, and 105ms for long sentences, ensuring instant translation capabilities.

*3) Translation accuracy:* The translation accuracy exceeds 95%, outperforming existing techniques by at least 5%.

These results validate the effectiveness and efficiency of the proposed interactive English oral automatic translation system.

## VII. CONCLUSION

Aiming at the problem of interactive spoken English translation, this study designs a new automatic translation system based on deep learning algorithm, optimizes both hardware and software, and mainly completes the following research:

Establish a deep learning translation mathematical model, and use the bus to connect the I/O bridge, recorder, interactive information collector and initial language correction unit to build a framework. The arithmetic logic unit (ALU) has extremely strong computing power and can calculate data information in a short time.

The hardware design is completed through the collector, encoder, interactive detector, interactive processor and decoder. The NAND-flash memory adopts nonlinear macro unit mode and has extremely high storage efficiency.

By using deep learning and a residual network to realize software translation, use the decoder to optimize the maximum output sequence, and insert blank tags in each frame of information to ensure that the information can be translated more accurately.

Experiments show that the translation system designed in this study can achieve accurate translation in a short time, and the translation success rate is higher than that of the traditional translation system. Although this study has the above advantages, it still faces many challenges, mainly in the following aspects:

Attribute mutations may occur during the process of customizing parameters, which may affect the operation sequence of training functions and calling functions.

Since the control flow logic cannot be completely recorded in the intermediate expression, the instant translation accepts fewer Python native statements. If this problem can be solved, the framework's expressiveness will be significantly improved.

For future work, we plan to investigate more advanced deep learning algorithms to further improve the translation accuracy and speed. Additionally, we will explore the integration of more sophisticated hardware components to optimize the system's performance.

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# Impact of Cryptocurrencies and Their Technological Infrastructure on Global Financial Regulation: Challenges for Regulators and New Regulations

Juan Chavez-Perez, Raquel Melgarejo-Espinoza, Victor Sevillano-Vega, Orlando Iparraguirre-Villanueva
Facultad De Ingeniería, Universidad Tecnológica Del Perú, Chimbote, Perú

***Abstract*—The rise of cryptocurrencies is transforming the landscape of global finance, but their very decentralized nature is triggering unprecedented challenges for regulatory systems. This systematic literature review (SLR) aimed to gather and synthesize information to understand the functioning of cryptocurrencies in relation to their regulatory challenges. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology supports the rigor of the research, where 50 studies published between 2022 and 2025 were selected in databases such as Scopus, Web of Science, IEEE Xplore and Science Direct. Among the results, it was observed that the continents with the greatest contributions were Europe and Asia, representing 60% and 25% of the studies analyzed, respectively. Likewise, the period with the highest scientific production was the year 2024, with 50% of the manuscripts published. Regarding the analysis of keyword co-occurrence using VOSviewer, it was found that "blockchain" and "cryptocurrency" were the most predominant terms, with 18 and 16 mentions, highlighting their centrality in the academic discussion. Ultimately, the research highlights that cryptocurrencies bring with them major regulatory challenges, such as money laundering and lack of legal clarity, while blockchain emerges as an essential tool to improve the transparency and operability of financial regulation.**

***Keywords*—Cryptocurrencies; financial regulation; blockchain; regulatory challenges; cryptocurrency laws**

## I. Introduction

For some years now, digital transformation has been playing a major role in the global economy. One of the emerging trends is cryptocurrencies, a new tradable asset capable of revolutionizing the way payments are made [1]. The innovation of its technology and its growing popularity are capturing the attention of the mainstream media and investors [2]. By 2023, more than 23,000 types of cryptocurrencies had been registered [3]. Their growth has exposed various regulatory challenges globally. According to the United Nations (UN), the decentralization of the network in which cryptocurrencies operate makes it difficult to regulate them within the existing legal framework and highlights the lack of legal clarity on procedural issues affecting transactions involving different countries [4]. Similarly, the World Health Organization (WHO) emphasizes the importance of establishing unambiguous measures as new technologies such as cryptocurrencies emerge, to develop functionalities that ensure security and accessibility [5]. The cryptocurrency market is positioning itself as a profitable activity for investors, as they find it very beneficial to acquire this asset class at relatively low prices for subsequent sales at higher values [6]. This type of web-based digital exchange has now become a popular commodity and an attractive source of trading [7].

The cryptocurrency landscape is very broad, within it, "Bitcoin", one of the most popular cryptocurrencies for being the pioneer in the field, reached in less than a decade a capitalization value of one trillion dollars and boosted the creation of more than 10,000 additional cryptocurrencies [8]. The secret of the success of this technology lies in its cryptographic protection, derived mainly from the combination of cutting-edge technologies and decentralized systems, such as blockchain [9]. Blockchain technology also provides a secure and verifiable system of record [10] allowing individuals to interact with electronic wallets that make it possible to store and manage their cryptoassets independently [11]. This type of technology allows the creation of a peer-to-peer network, which acts in combination with a cryptographic algorithm, distributed data storage and a decentralized consensus mechanism. On the other hand, there are also technologies such as artificial intelligence (AI), which is playing a remarkable transformation in financial systems, since they allow optimizing critical processes, as well as handling incidents by 63%, decreasing resolution time and improving operational effectiveness to increase user satisfaction by more than 50% [12]. These technological advances, although promising, pose regulatory challenges like those of cryptocurrencies, such as the need to monitor algorithms and ensure transparency in automated decision making.

The rapid increase in the diversification of cryptocurrencies has represented a deficiency in studies on their economic and regulatory impact. Currently, financial regulation does not adequately address key aspects such as digital wallet software, which has generated risks in terms of security and financial crime [13]. A worrying example is the use of cryptocurrencies in dark web markets, which have become the main means of payment for illicit activities, because various features allow instant payments without major costs, their addresses can be easily obtained and modified, transactions are highly anonymous, a feature that complicates the identification of individuals [14]. This situation has generated new regulatory challenges in terms of personal data management standards, trust and traceability of financial events [15].

This study is justified by the need for research that addresses the global regulatory challenges associated with

cryptocurrencies and explores the impact of blockchain technology on evolving financial regulations. The objective is to compile and synthesize recent scientific evidence to understand the risks inherent in these digital assets, identify emerging regulations, and propose recommendations for a more effective regulatory framework tailored to the dynamics of the global financial system.

This paper is organized as follows: Section II presents a literature review, focusing on the challenges and financial regulations related to cryptocurrencies. Section III describes the methodology used for the review, based on the PRISMA method. Section IV presents the main findings obtained. Section V discusses the results, and finally, Section VI presents the conclusions of the study.

## II. Literature Review

### A. Regulatory Challenges for Cryptocurrencies

Several studies have analyzed the impact of cryptocurrencies on global financial regulation. In the study [16], we evaluated the dynamics and risks associated with cryptocurrencies to explore the stylized facts, volatility and risk measures in the performance of digital assets, by using daily data of bitcoin, ripple and Ethereum, and their comparisons with technology stocks, risk measures such as Value-at-Risk (VaR) and Expected Shortfall (ES) were applied. The results confirmed that cryptocurrencies present high volatility, dependencies between cryptocurrencies, volatility clusters and arbitrage opportunities, highlighting that cryptocurrencies are riskier than technology stocks.

Similarly, in [17], evaluated the presence of speculative bubbles in the cryptocurrency market during the COVID-19 pandemic, analyzing the gregarious behavior of investors and factors such as Google searches and transaction volume, using probit regressions in time series and panels, together with alternative measures of liquidity and volatility. It was determined that all the cryptocurrencies analyzed presented bubbles, and that explosive behavior in one cryptocurrency affects others, contradicting the efficient market hypothesis. Complementarily, in [18], hybrid models combining forward propagating neural networks (DFFNN), and long term memory networks (LSTM) with generalized autoregressive conditional heteroskedasticity (GARCH) models were evaluated in three types (GARCH, EGARCH and APGARCH) with the objective of predicting the volatility associated with 27 cryptocurrencies, employing the outputs of the GARCH models as inputs to the neural networks, demonstrating that the hybrid models outperform the GARCH and deep learning (DL) models separately, significantly improving the accuracy in predicting volatility.

In [19], they analyzed tail risk in cryptocurrencies, non-fungible tokens (NFTs), stocks and gold, using conditional VaR-based models, showing that there is no superior model to capture tail risk, but non-Gaussian distributions better modeled skewness and heavy tails, which is crucial for risk management and portfolio diversification. In the same vein, in [20], the ability of volatility models to predict downside risk in cryptocurrency trading was explored by applying models such as conditional autoregressive VaR (CAViaR), dynamic quantile rank (DQR), GARCH and generalized autoregressive score (GAS) to five cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin and Stellar), evaluating forecasts using backtesting techniques and model confidence sets (MCS). The result showed that quantile-based models combined with a weighted aggregation method were the most effective in predicting downside risk.

### B. Financial Regulations Through the Influence of Cryptocurrencies and Blockchain

In the study [21], they sought to promote a greater focus on the analysis of cryptocurrencies as money within international political economy (IPE), employing monetary theories, such as the "commodity theory of money" and the "state theory of money", concluding that cryptocurrencies represent a challenge to traditional monetary theories and suggesting that their development as money is influenced by political dynamics that deserve further investigation. Likewise, in research [22], examined the existence of seasonal patterns in cryptocurrency returns, through data analysis of 500 cryptocurrencies, focusing on the Monday effect and trading activity during weekends. As a result it was found that the positive Monday effect on Bitcoin did not persist after 2015, and that there is no robust evidence of anomalies in returns, although trading activity was lower on weekends.

Consequently, in [23], explored the transmission of extreme risks between NFTs, DeFi tokens and cryptocurrencies, using the quantile connectivity technique to analyze volatility conditions was able to identify that NFTs offer greater diversification opportunities, with lower risks compared to other blockchain markets, making them an attractive option to reduce extreme risks. Complementarily, in [24], they analyzed how climate shocks affect extreme risks in cryptocurrency markets, for which they built risk contagion networks using a TVP-VAR model to measure the sensitivity of cryptocurrencies to climate, political and financial factors, finding that extreme risks in cryptocurrencies are highly sensitive to climate shocks, and that global financial markets are the main transmitters of risks. Furthermore, in [25], addressed the comparison of herding behavior in "clean" low-energy and "dirty" high-energy cryptocurrency markets, using the method of collecting data on market returns and activity, and by using value-weighted and equally-weighted portfolios, it was found that herding behavior is more pronounced in "dirty" markets, especially in bearish market conditions, while "clean" cryptocurrencies only showed herding behavior when both markets were rising. Table I shows the main findings and limitations of the reviewed studies.

TABLE I. CONCLUSIONS AND GAPS FOUND IN THE REVIEWED PAPERS

| Refs. | Main results | Limitations |
|---|---|---|
| [16] | Identify higher risk in cryptocurrencies using VaR and ES | It does not explore how financial regulations could mitigate these risks. |
| [17] | Detects speculative bubbles during COVID-19 using probit models and Google Trends | It does not analyze regulatory mechanisms to prevent bubbles. |
| [18] | Hybrid GARCH-LSTM models improve volatility prediction in 27 cryptos | It does not consider emerging regulations in the models. |
| [19] | Non-Gaussian distributions better model tail risk in cryptos vs. traditional assets | Does not discuss application to regulatory capital requirements. |
| [20] | CAViaR models outperform GARCH in predicting downside risk backtesting with MCS | Does not integrate with regulatory oversight systems. |
| [21] | Evidence of contradictions between cryptos and traditional monetary theories | It does not propose an adapted regulatory framework. |
| [22] | Refutes seasonal patterns in yields (500 cryptos analysis) | Does not evaluate the impact of market regulations. |
| [23] | NFTs show lower systemic risk than DeFi | It does not address specific regulation for NFTs. |
| [24] | Climate shocks increase systemic risk according to the TVP-VAR | It does not consider regulatory climate disclosure. |
| [25] | Increased gregarious behavior in "dirty" crypts (high energy consumption) | Does not analyze the impact of environmental policies. |

## III. METHODOLOGY

The study was guided by the PRISMA 2020 statement, widely recognized for its requirement in terms of rigor, transparency and relevance in conducting systematic reviews. The framework describes a concrete structure for identifying, selecting and synthesizing relevant studies, ensuring that the process is fully replicable and free of bias [26]. The application of PRISMA 2020 is essential to answer the research questions formulated, focusing on the regulatory challenges associated with cryptocurrencies and their influence on the evolution of international financial regulation. Complementarily, a graphical representation tool based on an R programming language and its Shiny package was used to build the flowchart. This allowed us to elaborate a clear visualization of the different phases of the process, covering from the initial collection of the studies to the final selection of the included documents, facilitating the comprehensive understanding of the procedure [27].

The research questions were developed based on a methodical and strictly structured process. The first step was to conduct a preliminary review of the existing literature regarding the subject matter of cryptocurrencies and financial regulatory standards, with the objective of identifying those trends, gaps and potential areas of interest. After this initial exploration it was detected that, although there are studies about the impact of cryptocurrencies on financial markets, there is a lack of publications addressing global regulatory challenges and the contribution of blockchain to the evolution of regulations in the field.

Based on this review, issues of current relevance were prioritized, and questions were formulated that not only reflect the most current problems in the field but also help to fill gaps in literature. The following are the research questions that were formulated to guide the study:

- What are the main regulatory challenges faced by the bodies in charge of supervising cryptocurrencies at a global level?
- How have cryptocurrencies and blockchain technology influenced the evolution of international financial regulations?

To ensure the suitability and quality of the selected studies, it was necessary to establish the relevant criteria to incorporate in-depth and specific research. These considerations are presented below:

### A. Inclusion Criteria

Studies that explore the regulatory challenges associated with cryptocurrencies or analyze the impact of blockchain technology on global financial regulation.

Research published in academic databases related to the topic, peer-reviewed journals or presented at recognized international conferences, ensuring academic rigor.

Publications between the period 2022 and 2025, to capture the most recent developments and debates in the field.

Articles written entirely in English, due to their international scope and standardization in the academic community.

### B. Exclusion Criteria

Studies published before 2022, as they may not reflect current developments and challenges in the cryptocurrency and blockchain ecosystem.

Research that does not directly address the main regulatory and technological aspects central to the study.

Articles that are not peer-reviewed or lack clear methodology and solid empirical evidence.

Papers that do not provide relevant information to answer the research questions posed.

The search for publications was carried out within academic databases relevant to the focus of the study, including Scopus, Web of Science, Science Direct and IEEE Xplore. Likewise, employing keywords such as cryptocurrencies, financial regulation, blockchain, regulatory challenges and cryptocurrency laws, together with Boolean operators and the period between 2022 and 2025, made it possible to ensure recent developments in the field and to gain insight into the various perspectives. The result of this process provided the compilation of an initial set of studies. Fig. 1 shows the distribution of these studies according to the source of origin, providing a complete overview of the number of publications identified.

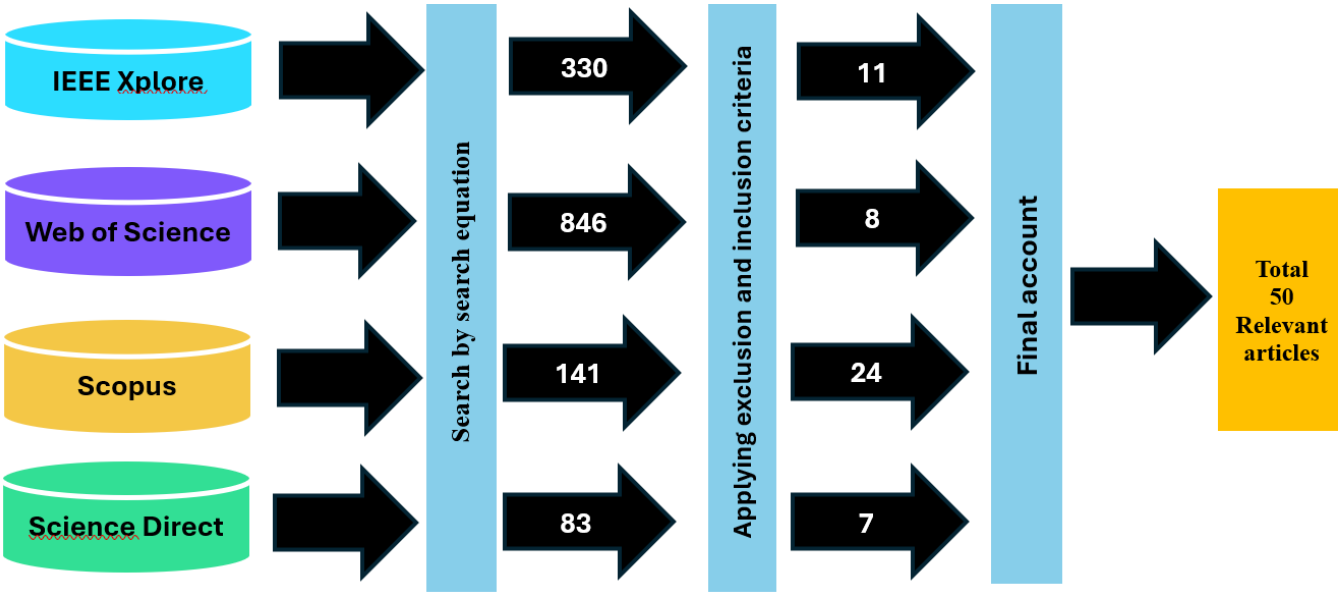



Fig. 1. Distribution of studies per database.

The PRISMA 2020 guidelines guided the process comprehensively, aligning under the framework is necessary to organize the SLR in four main phases, which are mentioned below:

- Identification: rigorous search of selected databases to identify potentially useful studies for addressing research questions.
- Selection: Filters were applied among the articles obtained, starting from the elimination of duplicate works and performing reviews based on title and abstract.
- Eligibility: To verify their relevance and materiality, the papers that passed the screening phase were subjected to an in-depth evaluation, in which it was verified that they adequately answered the research questions.
- Inclusion: The selection to be included for the review had to meet all the defined criteria, standing out for the finding in its literary information.

Fig. 2 illustrates in a synthesized way the selection process based on PRISMA 2020, mainly highlighting its organization in three key stages: identification, selection and inclusion. This visual representation expresses the sequential progression from the initial collection of studies to obtaining the final sample of those included, showing the gradual reduction of studies after the application of the established criteria.

Several computer tools were essential in the processing of the studies collected, since each of them played a strategic role throughout the different phases of the work. The Mendeley software made it possible to store and classify the documents according to their origin in the databases, contributing to the initial structuring of the set. The stored files were then exported in ".RIS" format and imported into Rayyan, a specialized resource platform for research work, whose incorporation made it possible to detect duplicities, create filters and apply them in an evolutionary manner. Through this tool it was possible to identify and eliminate 87 duplicate articles and discard 125 documents that did not meet the eligibility criteria, including systematic reviews, meta-analyses and other types of secondary literature. Subsequently, the selected studies to be included in the SLR were classified in Microsoft Excel, organizing them in a data matrix, recording key information such as the database of origin, title, year of publication, type of document, country of origin, methodological approach classified as qualitative, quantitative or mixed, and the answers to the research questions. This structure enabled a more thorough analysis of the 50 studies chosen, allowing the identification of patterns and trends relevant to the development of the research.

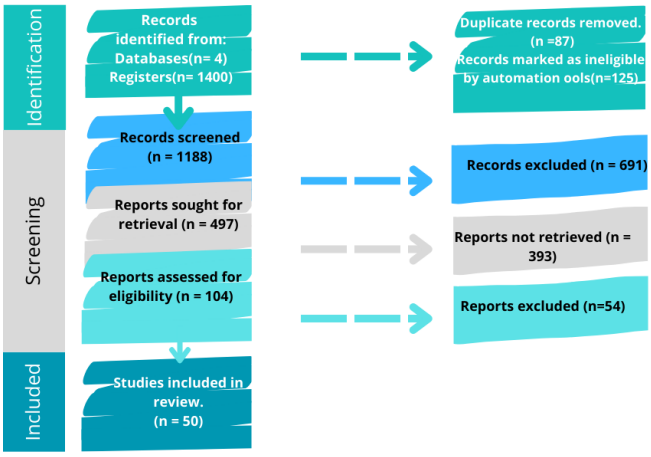



Fig. 2. PRISMA 2020 methodology.

## IV. Results

The results obtained provide a detailed overview, forming the basis for understanding how the latest scientific literature addresses the regulatory challenges of cryptocurrencies and their impact on the evolution of financial regulations. The

development of the stages of the screening process under PRISMA 2020 standards gradually contributed to improving the collected documents, so that it has been ensured that the final studies are the most relevant to represent the review. The initial compilation, presented in Table II, reflects the diversity of the sources consulted, laying a solid foundation for the subsequent analyses.

TABLE II. INITIAL DISTRIBUTION OF STUDIES BY DATABASE

| Database | Quantity | Percentage |
|---|---|---|
| Scopus | 141 | 10.07% |
| Web of Science | 846 | 60.43% |
| Science Direct | 83 | 5.93% |
| IEEE Xplore | 330 | 23.57% |
| | 1400 | 100% |

After collecting the studies, they were classified within collections created according to their source of origin provided by the academic databases. From that process, the exhaustive analysis of the documents began, starting the filtering phases for inclusion and exclusion.

### A. Phase 1: Elimination of Duplicates and Initial Filters

The first phase develops the debugging of duplicates and secondary documents that could have been included after compilation. Therefore, the full detection functionality provided by Rayyan is run, resulting in the consolidation of a refined set of 1,188 unique studies, excluding 212 non-representative ones. The reduction allowed optimizing the database, eliminating redundancies that could distort the analysis, in addition, it was possible to highlight Web of Science as the most representative source in the set, thanks to its high percentage value, followed by IEEE Xplore, Scopus and Science Direct, as detailed in Table III, which reflects the first significant transformation in the analyzed dataset.

TABLE III. DISTRIBUTION OF STUDIES AFTER ELIMINATION OF DUPLICATES AND INITIAL FILTERS

| Database | Quantity | Percentage |
|---|---|---|
| Scopus | 119 | 10.02% |
| Web of Science | 732 | 61.62% |
| Science Direct | 70 | 5.89% |
| IEEE Xplore | 267 | 22.47% |
| Total | 1,188 | 100% |

### B. Phase 2: Review of Titles and Keywords

The review of the 1,188 documents remaining up to this stage, using titles and key words, made it possible to identify those that maintained an evident and concrete link with the research questions posed. As a result of this analysis process, 691 documents were discarded because they did not address the central theme of the focus of the study, since they were outside the limits established in the framework. As a result of this filtering, the set of documents was reduced to 497 records. Table IV shows the updated distribution of the studies after this phase, showing the new proportional configuration between the databases.

TABLE IV. DISTRIBUTION OF STUDIES AFTER REVISION OF KEY TERMINOLOGY IN TITLES

| Database | Quantity | Percentage |
|---|---|---|
| Scopus | 70 | 14.08% |
| Web of Science | 225 | 45.27% |
| Science Direct | 29 | 5.84% |
| IEEE Xplore | 173 | 34.81% |
| Total | 497 | 100% |

Subsequently, we proceeded to a more exhaustive review of the 497 documents, focusing objectively on the analysis of the summaries provided by the studies, but full texts were addressed in those that presented little information in their abstracts.

### C. Phase 3: Review of Abstracts and Full Text

From this process, the analysis had to check those studies that accurately addressed the regulatory challenges of cryptocurrencies and how the impact of blockchain technology was affecting financial regulations. To do so, strategic keywords had to be used such as: cryptocurrencies, blockchain, digital currencies, regulatory challenges, DeFi and empirical study.

The result was the exclusion of 393 studies for not meeting the criteria, so that the set was reduced to 104, firmly refining the literature base for the final analysis. In this line, it was highlighted that the evolution of the studies belonging to Scopus for this stage showed that their content was relevant after their respective evaluation, thus emerging as the one that eliminated the least number of documents. Table V presents the updated distribution of the studies after this phase, reflecting this transformation in the composition of the final sample.

TABLE V. DISTRIBUTION OF STUDIES AFTER ABSTRACT AND FULL TEXT REVIEWS

| Database | Quantity | Percentage |
|---|---|---|
| Scopus | 26 | 25% |
| Web of Science | 41 | 39.42% |
| Science Direct | 14 | 13.46% |
| IEEE Xplore | 23 | 22.12% |
| Total | 104 | 100% |

### D. Phase 4: Final Inclusion

The last selective procedure, aimed at closing the studies for definitive inclusion, consisted of assessing the depth of the content, specifically the degree of complementarity with the methodological soundness and relevance of the contributions to the research approach and the questions formulated. Thus, 54 studies were excluded because they failed to provide substantial evidence and because they presented methodological limitations that compromised their validity in the context of the present study. Therefore, the final set was composed of 50 studies that rigorously met the established criteria, ensuring a robust and representative database for subsequent analyses.

TABLE VI. FINAL DISTRIBUTION INCLUDING STUDIES

| Database | Quantity | Percentage |
|---|---|---|
| Scopus | 24 | 48% |
| Web of Science | 8 | 16% |
| Science Direct | 7 | 14% |
| IEEE Xplore | 11 | 22% |
| Total | 50 | 100% |

Regarding the final distribution of the chosen studies, the Scopus source predominated, followed by IEEE Xplore, Web of Science and Science Direct, reflecting a diverse and balanced composition of the specialized literature. Table VI illustrates this final distribution, consolidating the result of the systematic selection process.

To complement the collection of the 50 studies chosen in this review, a visual representation of the complete distribution is included through a bar graph, showing the numerical data for each academic database selected for the work. Fig. 3 not only facilitates the interpretation of the final set of data but also provides a clear and accessible perspective on the provenance of the selected literature.

Once the final studies were obtained, processes were carried out to determine certain aspects of relevance for the research. Starting with the temporal distribution, which covered the period from 2022 to 2025, where an increasing trend in academic production related to the subject of study was evidenced. Likewise, by 2022, 8 studies were identified, representing 16%. On the other hand, the number increased significantly in 2023, with a value of 13, representing 26%. The trend continued to increase in 2024, with the highest production of 25% of the set, equivalent to 50%. In contrast, in 2025, 4 studies were disclosed, representing 8% of the total. It is important to note that, as 2025 progresses, an increase in the number of published studies is expected. Fig. 4 illustrates this temporal distribution, highlighting the evolution of academic production and the importance of the studies published in the most recent period.

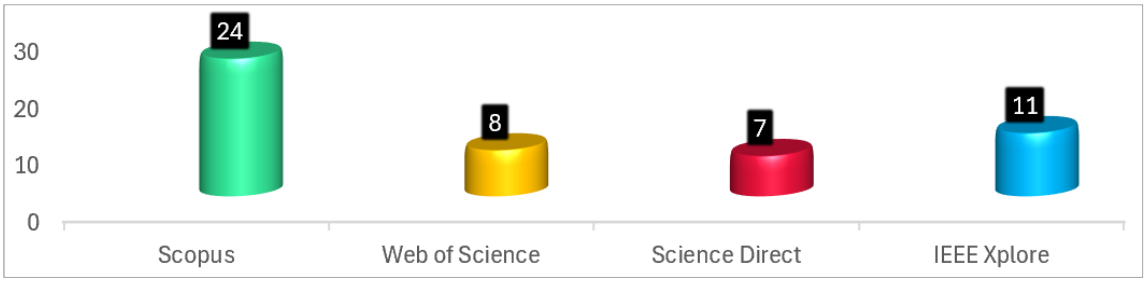



Fig. 3. Distribution of studies included by each database.

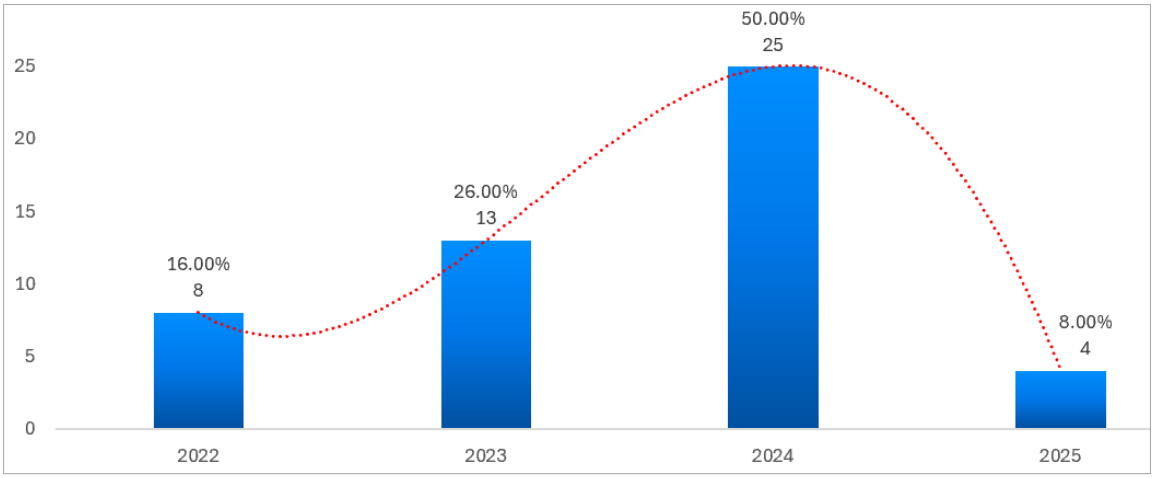
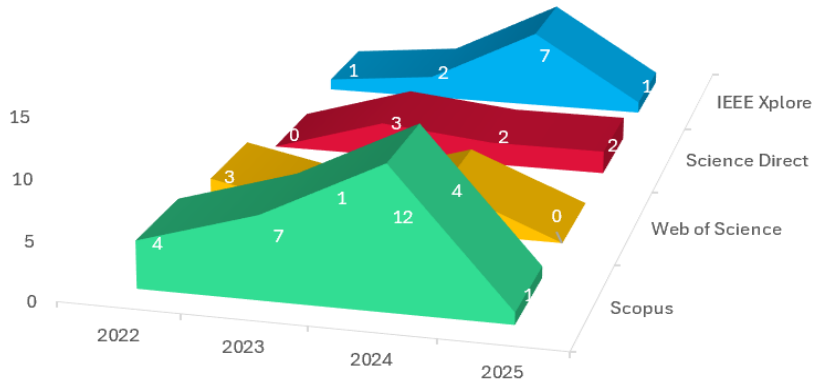



Fig. 4. Studies by year of publication.

In the same line, the time frame was relevant to determine the scientific production of studies associated with their respective databases. The most remarkable result was the contribution of Scopus in the year 2024, since it represented 12 studies, consolidating its relevance to the field as the main source in research. In the same line, IEEE Xplore showed its contribution with 7, Web of Science with 4 and Science Direct with 2. On the other hand, manifesting contributions in previous years, Scopus maintained its predominance in 2023 with 7 studies, while Science Direct and IEEE Xplore contributed with 3 and 2 respectively, and Web of Science with 1. As for the year 2022, the contributions were established with Scopus with 4, Web of Science with 3, IEEE Xplore with 1 and Science Direct with no records. On the other hand, for the most current year of 2025, the contributions with literary presence up to the present were constituted by Science Direct in 2 and IEEE Xplore in 1 study, while Scopus registered 1 and Web of Science did not present contributions. Fig. 5 illustrates the proportional trend, highlighting the contribution of each database over time.




| | 2022 | 2023 | 2024 | 2025 |
|---|---|---|---|---|
| Scopus | 4 | 7 | 12 | 1 |
| Web of Science | 3 | 1 | 4 | 0 |
| Science Direct | 0 | 3 | 2 | 2 |
| IEEE Xplore | 1 | 2 | 7 | 1 |

Fig. 5. Distribution of studies by year and databases.

As for the geographical origin of the SLR studies, the analysis showed that there was a strong prominence of countries with more developed financial systems, which have active regulatory frameworks for cryptocurrencies. The United Kingdom tops the list with 6 studies, representing 12% of the total, followed by China with 5 studies, corresponding to 10%, and Indonesia and Ukraine with 4 studies each, corresponding to 8%. Denmark, Estonia, Germany, Pakistan, Russia, Saudi Arabia and the United States are ranked with 2 studies each, representing 4%. In contrast, Australia, Bangladesh, Belgium, India, Italy, Hungary, Kazakhstan, Lithuania, Luxembourg, Malaysia, Mauritius, Mexico, Morocco, Netherlands, Poland, Spain and Taiwan have 1 study each, equivalent to 2%. In view of the results, it can be stated that the academic production is higher in the regions of Europe with 60% and Asia at 25%, surely because of their concern for cryptocurrency regulation and financial development. Likewise, the low participation of Latin America and Africa suggests less attention to the treatment of the object of study in these regions. Fig. 6 provides a detailed geographical breakdown of the studies on the issue.

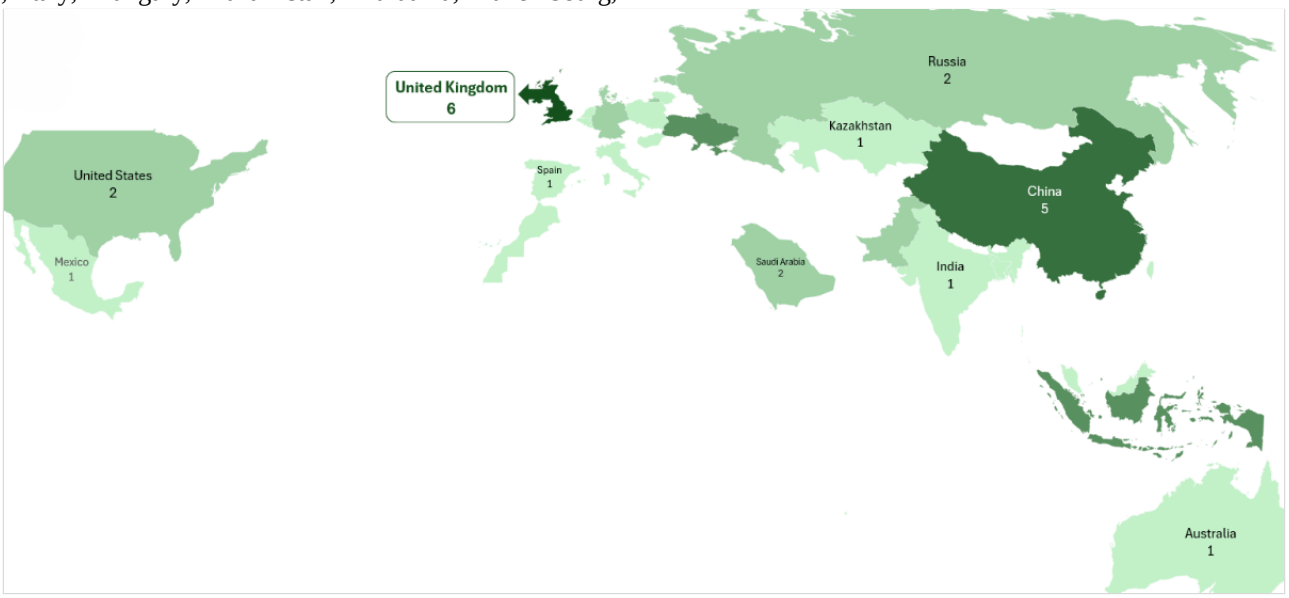



Fig. 6. Origin of studies by geographic region.

The review of each study included in this research revealed that 100% of the studies correspond exclusively to journal articles. This concentration reflects the prominence of scientific publications when studying the subject of interest regarding cryptocurrencies and their regulatory implications, reflecting the prominent role of this format in the generation and dissemination of knowledge. However, it is imperative that the need to develop more applicable approaches in other fields to overcome the gap originated by the absence of other types of publications, such as conference proceedings and technical reports.

The methodological approach used in the studies reviewed shows a preponderance of qualitative approaches, with a notable representation in the main databases. In this regard, the main reference was Scopus, which presented 18 qualitative studies, equivalent to 36%, followed by Web of Science and Science Direct with 6 studies each, equivalent to 12%, while IEEE Xplore contributed 2 studies, with 4%. The quantitative strategy had less presence, with IEEE Xplore standing out with 6 papers, representing 12%, Scopus with 3, 6%, and Web of Science 1, 2%, while Science Direct had no quantitative studies. The mixed method showed a more limited rate of representation, since Scopus and IEEE Xplore recorded 3 studies respectively, which accounted for 6%, and Web of Science and Science Direct only 1 study, which equaled 2%. The results indicate that research on cryptocurrencies and financial regulation is mainly based on qualitative analyses, most likely due to the need to interpret regulatory frameworks and economic trends. Fig. 7 presents in detail the distribution of methodological approaches used in the analyzed studies.

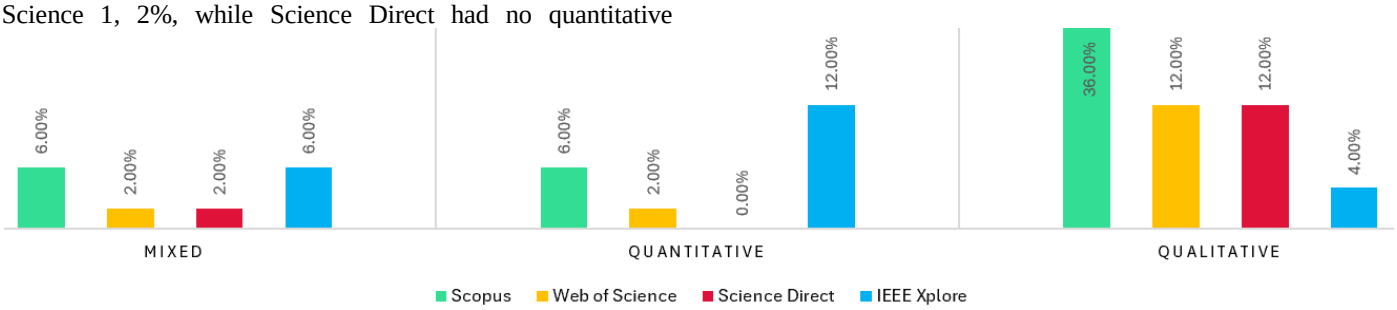



Fig. 7. Studies by methodological approach.

Finally, with the support of the "VOSviewer" software tool for the identification of keywords, considering their level of co-occurrence and representing the relationships between existing within the analyzed corpus. For this purpose, the software analyzed the keywords assigned by the authors, terms included in the titles and the summary content. In the results obtained it was found that "blockchain" and "cryptocurrency" constitute the most predominant concepts, with 18 and 16 mentions respectively, which reaffirms their central role in the academic discussion.

The thematic groups interconnected by cluster analysis reflected different perspectives of the phenomenon studied. The yellow cluster addressed digital infrastructure and asset security, highlighting terms such as "distributed ledger technology" and "digital assets market", elements that underline the importance of decentralized accounting systems. In contrast, the blue cluster focused on regulation and compliance, with terms such as "money laundering", "fintech" and "regulation", highlighting the challenge of establishing suitable legal frameworks for cryptocurrencies. Finally, the brown cluster encompassed key words such as "financial crime" and "policy", highlighting concerns about the relationship between cryptoassets and financial crime. Fig. 8 illustrates the distribution of these clusters, highlighting mainly keywords in a visual representation of the main areas of study identified in the literature.

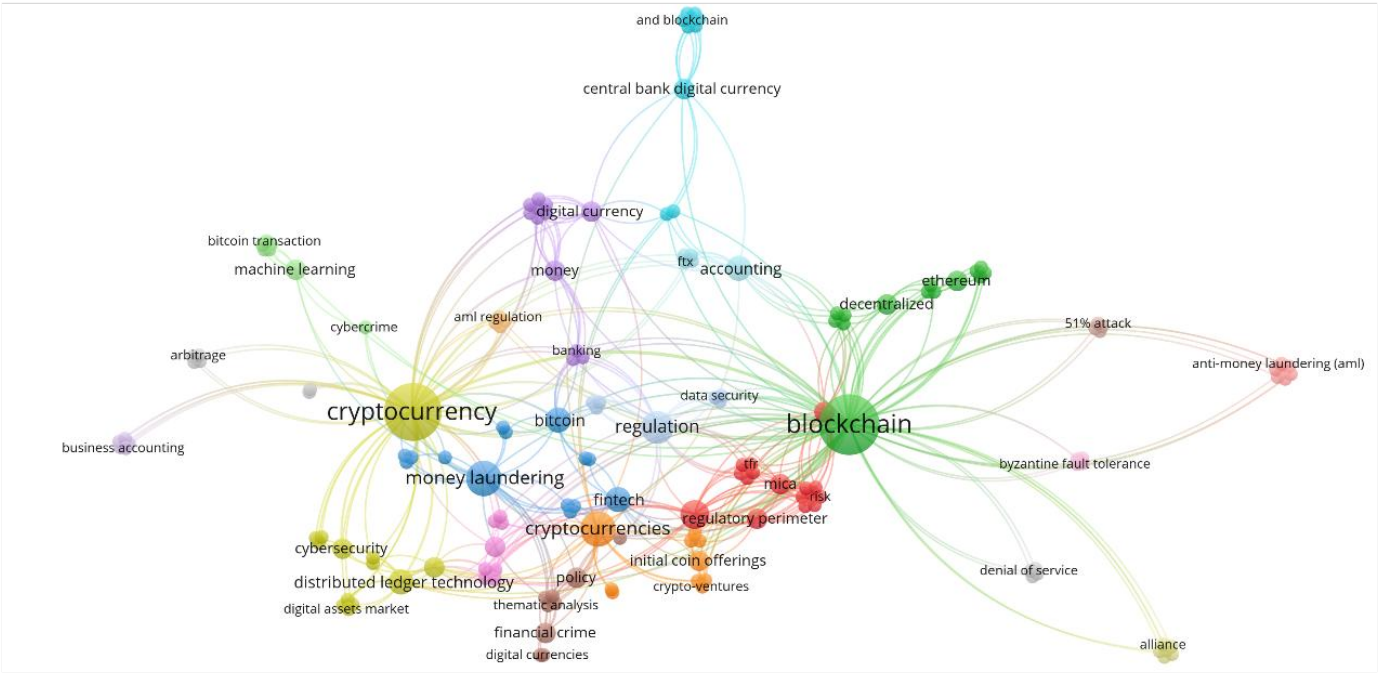



Fig. 8. Exploration of co-occurrence in literature.

## V. DISCUSSIONS

### A. Q1: What are the Main Regulatory Challenges Facing the Bodies in Charge of Overseeing Cryptocurrencies Globally?

The growing adoption of cryptocurrencies brings with it governmental and institutional attention around the world. The purely speculative origin and their movements in conditions of anonymity contribute to challenges such as money laundering, lack of legal clarity and regulatory differences. In this sense, the study [16], addressed the risk associated with cryptocurrencies, evaluating their dynamics and volatility through daily data and metrics such as VaR and ES, showing that cryptocurrencies exhibit high volatility rates and high dependence, a fact that, in addition to suggesting arbitrage opportunities, highlights their potential to facilitate activities such as money laundering due to the difficulty of tracing anonymous transactions. On the other hand, research [17] examined the formation of speculative bubbles and herd behavior in the cryptocurrency market during the COVID-19 pandemic. Through probit regressions, alternative metrics of liquidity and volatility, they managed to identify that all the cryptocurrencies analyzed presented speculative bubbles. On the other hand, the paper [19] analyzed tail risk in cryptocurrencies, NFTs, stocks and gold, for which they used conditional models based on VaR, as a result it was revealed that there is no single superior model to capture extreme risk; however, it was observed that non-Gaussian distributions proved to be more effective when modeling asymmetry and heavy tails in returns. This reinforces the need to address the lack of legal clarity in the regulation of these assets, as the absence of clear standards increases risk exposure and hinders the implementation of effective regulatory frameworks.

Also, regarding volatility prediction, the study [18] combined neural networks such as DFFNNN and LSTM with GARCH models in three types such as (GARCH, EGARCH and APGARCH) to analyze 27 cryptocurrencies, using the outputs of GARCH models as input data for the neural models, and showed that the hybrid models performed better than the individual models in terms of accuracy. Furthermore, [20] studied the ability of volatility models to predict downside risk in cryptocurrency trading, using models such as CAViaR, DQR, GARCH and GAS to five cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin and Stellar), and using back testing and MCS techniques, it was concluded that quantile-based models, combined with a weighted aggregation method, are the most effective in anticipating the decline in the value of cryptocurrencies. Such a method allows highlighting regulatory discrepancies, as the lack of unified regulation hinders the implementation of effective risk management strategies. Below, in Table VII, the challenges in the regulatory arena found after the rigorous analysis are presented.

The results shows that cryptocurrency transactions have generated a wide range of regulatory challenges, many of which are interconnected. On the other hand, the decentralization and anonymity inherent in these technologies pose considerable hurdles for regulators, as they make it difficult to identify participants and track transactions. The problem arises especially in the case of stablecoins and DeFi platforms, since their rapid growth and technical complexity exceed the capacity of regulators to establish effective controls. Added to this is the increase in fraud and scams within the ecosystem in which cryptocurrencies operate, a phenomenon that has exposed vulnerabilities in the protection of users and the security of blockchain platforms. In addition to affecting investor confidence, this phenomenon poses significant risks to the integrity of financial markets. In particular, the taxation of cryptocurrencies remains a critical area due to the lack of accurate transparent reporting mechanisms and monitoring in the verification of transactions. This situation is compounded by the absence of standardized international rules, creating an environment in which illicit activities can flourish.

TABLE VII. CHALLENGES FOR REGULATORY AGENCIES

| # | Regulatory Challenge | Quantity | References |
|---|---|---|---|
| 1 | Money laundering | 6 | [28], [29], [30], [31], [32], [33] |
| 2 | Lack of legal clarity | 5 | [34], [35], [36], [37], [38] |
| 3 | Regulatory differences | 5 | [39], [40], [41], [42], [43] |
| 4 | Decentralization and anonymity | 5 | [44], [45], [46], [47], [48] |
| 5 | Stablecoins and DeFi | 5 | [49], [50], [51], [52], [53] |
| 6 | Fraud and protection | 5 | [54], [55], [56], [57], [58] |
| 7 | Blockchain security | 5 | [59], [60], [61], [62], [63] |
| 8 | Crypto taxation | 4 | [64], [65], [66], [67] |
| 9 | Transparency and monitoring | 4 | [68], [69], [70], [71] |

These challenges underscore the urgent need to develop robust and cooperative regulatory frameworks that address both current and emerging risks. The implementation of innovative solutions, together with strengthened international cooperation, will be essential to promote the creation of a safe, efficient and more transparent financial ecosystem.

### B. Q2: How have Cryptocurrencies and Blockchain Technology Influenced the Evolution of International Financial Regulations?

Cryptocurrencies have been greatly affected by the evolution of international financial regulation, as they pose regulatory challenges due to their decentralized and anonymous nature. Therefore, incorporating blockchain as a technological solution to support regulation is an essential strategy to balance innovation and regulatory control. In this way, this synergistic relationship enables regulators to develop more robust regulations tailored to the needs of the global financial system. These include those related to stability and governance, where blockchain enables real-time audits and decentralized governance systems (DAO), as well as supervision, where it improves transparency and ensures an immutable transaction history. Recent studies support this position, highlighting blockchain's ability to strengthen financial traceability and facilitate regulatory adaptation among dynamic digital environments.

In [23], the transmission of extreme risks between NFTs, DeFi tokens and cryptocurrencies was explored using the quant connectivity technique to analyze volatility conditions,

identifying that the NFTs offer greater opportunities to diversify and reduce risk levels compared to other blockchain markets, making them an alternative of interest to reduce extreme risks. The finding, together with the inherent traceability of blockchain, influences the creation of regulations that promote stability and governance in the cryptocurrency ecosystem, as well as the implementation of blockchain-based online auditing systems.

On the other hand, in [24], it was analyzed how climate shocks affect extreme risks in cryptocurrency markets, building risk contagion networks using a TVP-VAR model, whose results showed that cryptocurrencies are highly sensitive to climatic, political factors and that global financial markets are the main transmitters of risks. This has led regulators to strengthen oversight mechanisms and use blockchain technology to improve transparency and immutable transaction recording, thus mitigating associated risks. Also, Table VIII presents the impact of cryptocurrencies and blockchain on various financial regulations.

TABLE VIII. IMPACT OF CRYPTOCURRENCIES AND BLOCKCHAIN ON FINANCIAL REGULATION

| # | Impact of Cryptocurrencies | Blockchain Impact | Quantity | References |
|---|---|---|---|---|
| 1 | Stability and governance | Audits | 5 | [50], [56], [72], [73], [74] |
| 2 | Supervision | Traceability | 5 | [43], [66], [67], [70] |
| 3 | DeFi and Anti-Money Laundering (AML) Regulation | Compliance | 4 | [28], [68], [75], [76] |
| 5 | Financial innovation | Regulations | 4 | [35], [49], [54], [77] |

In terms with slight influence, DeFi and AML regulation stand out, where blockchain facilitates traceability, process automation and financial innovation, whose operation allows the implementation of regulations based on smart contracts. The study [25], compared gregarious behavior in "clean" and "dirty" cryptocurrency markets using profitability and market activity data. As a result, it was observed that herding behavior is more pronounced in "dirty" markets, especially in bearish market conditions. Similarly, in [22], seasonal patterns in cryptocurrency returns were examined by analyzing data from 500 cryptocurrencies and focusing on the effect of Monday and weekend trading activity, showing that a positive Monday effect on Bitcoin did not last after 2015, which has led regulators to consider financial innovation in designing smart contract-based regulations, enabling more efficient and transparent compliance in DeFi and AML regulations.

The influence of cryptocurrencies and blockchain technology on the evolution of international financial regulation is undeniable due to their nature in relation to their operations. Through traceability, real-time audits, automated compliance and DAO, blockchain not only mitigates the risks arising from cryptocurrencies, but also promotes transparency, efficiency and innovation for the global financial system. All of these developments underscore the importance of regulators harnessing the potential of existing technologies, such as blockchain and other emerging technologies, to support a transformative new system that the masses are migrating towards; achieving this will ensure the stability and integrity of financial markets.

## VI. CONCLUSION

In this SLR, the technological infrastructure within the cryptocurrency ecosystem was analyzed to identify its behavior in relation to the entities that regulate finance worldwide, taking as evidence the inclusion of 50 studies published between 2022 and 2025. The studies collected came from databases of recognized solvency for their prestige, such as Scopus with 24 articles, representing 48%, Web of Science with 8 equivalents to 16%, IEEE Xplore with 11 at 22%, and Science Direct with 7 representing 14%. The variety of these sources of information provides a complete and representative perspective of the current state of research in the field.

The results revealed that cryptocurrencies raise significant regulatory challenges, including money laundering, lack of legal clarity, decentralization and anonymity. It was also identified that blockchain technology is instrumental in improving transparency, traceability and regulatory efficiency. These findings underscore the need for innovative regulatory frameworks to balance technological innovation with user protection and financial stability. Moreover, it was reflected that the lack of unified international standards hinders the implementation of effective regulations, thus underlining the importance of global collaboration in this field.

This systematic study provides a solid foundation for future research to be undertaken by experts, as it synthesizes recent statistics and proposes priority areas for study, raising awareness. These areas include the development of flexible regulatory systems, comparative approaches across regions and the incorporation of new technologies into financial regulation. The findings also provide valuable input to regulators and policy makers, helping to create more effective regulations that are adaptable to current realities. However, the research faced limitations inherent to the study of emerging and disruptive issues. On the other hand, the rapid evolution of the cryptocurrency and blockchain ecosystem generated a gap between the literature findings and the current reality, suggesting the need for periodic updates in future reviews. Also, some studies presented methodological heterogeneity that hindered the comparability of results, so it is important to standardize approaches. Finally, the absolute lack of comprehensive papers addressing global regulatory challenges to financial regulation indicates a critical area for further research.

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# Developing a Comprehensive NLP Framework for Indigenous Dialect Documentation and Revitalization

Mohammed Fakhreldin
Department of Computer Science-College of Engineering and Computer Science, Jazan University, Jazan 45142, Saudi Arabia

***Abstract*—The disappearance of Indigenous languages results in a decrease in cultural diversity, hence making the preservation of these languages extremely important. Conventional methods of documentation are lengthy, and the present AI solutions somehow do not deliver due to data scarcity, dialectal variation, and poor adaptability to low-resource languages. A novel NLP framework is being proposed to solve the existing problems. This framework intermixes Meta-Learning and Contrastive Learning to counter these problems. Thus, adaptation to low-resourced languages becomes rapid via meta-learning (MAML), while dialect differentiation is enhanced through contrastive learning. The model training is carried out on Tatoeba (text) and Mozilla Common Voice (speech) datasets to ensure robust performance in both text and phonetic tasks. The results indicate that there is a reduction of 15% in Word Error Rate (WER), an 18% improvement in BLEU score corresponding to translation, and a 12% improvement in F1-score related to dialect classification. The testing was also done with native speakers to assess its practical viability. It is a real-time translation, transcription, and language documentation system deployed via a cloud-based platform, thereby reaching out to Indigenous communities globally. This dual-learning framework represents a scalable, adaptive, and cost-efficient solution for the revitalization of languages. The models proposed have been a game changer for language preservation, have set new standards for low-resource NLP, and have made some tangible contributions towards the digital sustainability of endangered dialects.**

***Keywords*—*Indigenous language preservation; natural language processing; meta-learning; contrastive learning; low-resource languages***

## I. Introduction

The rapid expansion of e-commerce has significantly impacted consumers' shopping behaviors, and augmented reality (AR) has been a key technology in optimizing users' interaction and minimizing return charges [1]. Normally, it lacks the touch and vision experience of store shopping, leading to confusion in consumers' choices and increased possibilities of product returns. AR closes the gap by allowing consumers to see products in real-life situations prior to buying, building confidence in their purchase decisions [2], [3]. Research has established that AR platforms profoundly increase consumer trust, interactivity [4] and product value perception, thus becoming a valuable tool for e-commerce firms to gain optimum sales and customer loyalty [5] [6]. Using AR not only optimizes interaction but also overcomes basic problems such as product misrepresentation and expectation discrepancies, which are leading causes of return rates on online shopping [7].

Including AR in online stores transforms online shopping by improving consumer engagement using immersive and personalized experiences. The technology allows for real-time interaction of customers with virtual products, enabling them to measure dimensions, touch, and fit, which cannot be done with standard images and videos [8] [9]. Besides, the psychological impact of trying products through AR significantly impacts buying intention as the customer develops a deeper emotional connection with the product, reducing hesitation to buy [10]. From a business perspective, AR-enabled platforms enhance customer satisfaction, increase conversion rates, and lower return-related logistics expenses [11]. The reduction in product returns not only lowers the financial losses of retailers but also enhances environmental sustainability by minimizing waste and carbon emissions caused by reverse logistics. As competition intensifies in the digital retail landscape, companies that invest in AR-based customer experiences gain a competitive advantage by instilling greater brand loyalty and mitigating post-purchase dissatisfaction [12].

Though it has several advantages, e-commerce adoption of AR is threatened by several issues, such as technology limitations, over-the-top implementation costs, and consumer adoption barriers [13]. Its success relies on advanced computer vision, AI, and real-time rendering capabilities, which require tremendous investment in development and infrastructure[14] [15]. Additionally, the adoption of AR technology by users varies based on factors such as digital literacy, device compatibility, and access to the Internet. There are also privacy concerns that arise from the data collection for personalization in AR, which raises ethical concerns about data privacy and consent. All these concerns have to be addressed through collaborative work between technology pioneers, retailers, and policymakers to create accessible, affordable, and privacy-compliant AR solutions as research continues to explore novel ways of optimizing [16].

The Key Contributions are as follows:

- It presents a new method combining Meta-Learning (MAML) for adaptation in low-resource languages and Contrastive Learning for better dialect distinction, solving linguistic diversity issues.
- To develop a strong NLP model-based documentation of indigenous languages from limited resources.
- To incorporate meta-learning for speedy adaptation of dialects and integrating contrastive learning for identifying dialects.

- The presented research provides the basis for a scalable and economical AI-oriented framework for endangered languages revitalization, permitting equity in digital media and preserving culture.

## II. Related Works

Pinhanez et al. [17] explored the role of AI and NLP, especially large language models, in documenting and revitalizing endangered Indigenous languages. The paper revealed a global decline in linguistic diversity, along with ethical concerns regarding the use of AI in language preservation. The authors suggested an AI development cycle that should be based on the integration of community involvement in real-world deployment that shows fine-tuning state-of-the-art translation models on small datasets produces promising results for the so-called low-resource languages. Prototypes co-developed with Indigenous communities in Brazil included spelling checker tools, next-word predictors, and other language support functions. The study then suggested scalable interactive language models for language preservation and offered replicable frameworks to researchers and policymakers.

Zhang et al. [18] deliberated on the role of NLP in restoring endangered languages. They observed that over 43% of endangered languages in the world today face threats from globalization and neocolonialism. The three guidelines proposed by the authors as part of their promotion of linguistic diversity are for ethical and respectful collaboration with Indigenous peoples. The authors also identified three applications of NLP: the language learning tech, speech recognition, and text systems, and practically illustrated such works with the case of the Cherokee language using methods machine-in-the-loop in support of language documentation.

Tan Le et al. [19] proposed a deep learning approach to morphological segmentation of polysynthetic Indigenous languages, focusing on Innu-Aimun spoken in Canada. Such languages have complex morphology and dialect variation, with limited resources. The approach differed from rule-based methods in that it used an abstract neural encoding of linguistic patterns, thereby improving segmentation accuracy and showing the potential of AI in handling morphologically rich languages.

Gedeon et al. [20] investigated the applications of NLP and AI in the preservation of the Shi language of the DRC, endangered with generational language shift. The study synthesized existing linguistic resources and outlined a plan in support of Shi through transcription, translation, and documentation tools, emphasizing the greater mandate of AI in language conservation.

Li et al. [21] proposed the MetaCL meta-learning approach that is optimized for few-shot learning in low-resource contexts where no complex models or prior knowledge are required. In terms of architecture, it consists of distorted sample episodes and unsupervised loss functions that utilize soft-whitening and soft alignment. CUB and mini-ImageNet experiments revealed that this novel approach outperformed other state-of-the-art methods, thus making it a simple but effective baseline.

Tan and Koehn [22] used a contrastive learning framework for clean bitext extraction in low-resource languages. They have shown how fine-tuning sentence embeddings with multiple negative ranking losses can provide better alignment and/or less noise in translation pairs. Their work on Khmer and Pashto demonstrates that this approach is effective in improving machine translation data quality.

Khatri et al. [23] compared multilingual learning with meta-learning when training models for new language pairs in low-resource NMT. Although both methods performed quite well, meta-learning was relatively better with a smaller amount of data, such as for Oriya-Punjabi, highlighting the way it is used in lower-resource settings.

Zhao et al. [24] proposed MemIML, a meta-learning framework to tackle memorization overfitting in low-resource NLP tasks. It incorporated task-specific memory and imitation modules while making MemIML boost the model's generalization by relying more on support sets. Theoretical validation was found effective in sparse data settings.

Tonja et al. [25] explained how technology renders Indigenous language communities obsolete with inducted urgency, marking these languages' cultural importance. It advocates incorporating these Indigenous aspirations within any NLP development. The paper then looks at the progress of NLP made regarding Latin American Indigenous languages, outlining challenges such as limited availability of data and community participation.

Vasselli et al. [26] presented a hybrid rule-based with prompt-based NLP for generating educational materials in the Maya and Bribri languages for the AmericasNLP 2024 Shared Task. Such an approach is precisely the answer to the issues of small corpora and the surface complexity of morphology. The model combined the linguistic accuracy of rule-based production with the capabilities of LLMs in contextualness. The approach is scalable to other Indigenous languages.

## III. Problem Statement

The lack of Native languages is a world concern, as many languages are threatened with extinction due to globalization, urbanization, and linguistic dominance by common languages. Loss of languages not only puts cultural heritage at risk but also leads to loss of linguistic diversity, which is the foundation of human knowledge and identity. Among the primary issues of concern in documenting endangered Indigenous languages is the lack of adequate linguistic resources, e.g., digitized texts, dictionaries, and linguistic corpora. Language documentation has historically been time-consuming and labor-intensive and generally requires substantial knowledge of linguistics as well as the target language. Artificial intelligence (AI) and natural language processing (NLP) can mitigate this issue. However, state-of-the-art AI models are primarily trained on high-resource languages and are, therefore, not very effective in processing low-resource Indigenous languages with complex linguistic structures [27]. Morphological variation, spelling variation, phonemic variation, and dialect variation contribute to the complexity of developing AI-based language tools [25].

## IV. PROPOSED METHODOLOGY

The suggested NLP solution to Indigenous dialect conservation uses a stringent methodology, combining Meta-Learning and Contrastive Learning for greater flexibility and dialect variation modeling. The methodology starts with data collection from the Tatoeba Dataset, offering parallel translations of low-resource language, and the Mozilla Common Voice Dataset, offering speech samples with diversity across dialects. Data pre-processing involves text normalization, phoneme extraction, and diarylation of speakers to provide the model with clean and formatted inputs for training. For promoting language flexibility, Meta-Learning (MAML) is employed on the Tatoeba dataset so that NLP models can effectively adapt to learning low-resource native languages quickly. The approach adapts multi-task learning for optimal generalization. In contrast, Contrastive Learning is applied to the Mozilla Common Voice corpus to learn dialect distinctions by minimizing intra-class variation and maximizing inter-class difference. It is optimized through AdamW with learning rates that adapt to improve convergence. BLEU, WER, and F1-score are the evaluation metrics to ensure linguistic accuracy and dialect homogeneity. Lastly, deployment of the model embeds the trained model in an API-based platform that provides real-time translation and transcription services for aboriginal dialects. The model in deployment achieves access across both mobile and web interfaces, enhancing language preservation. The approach thus presents a scalable, adaptive, and efficient strategy to revive the threatened languages utilizing state-of-the-art NLP methodologies. The overall architecture of the proposed framework is illustrated in Fig. 1.

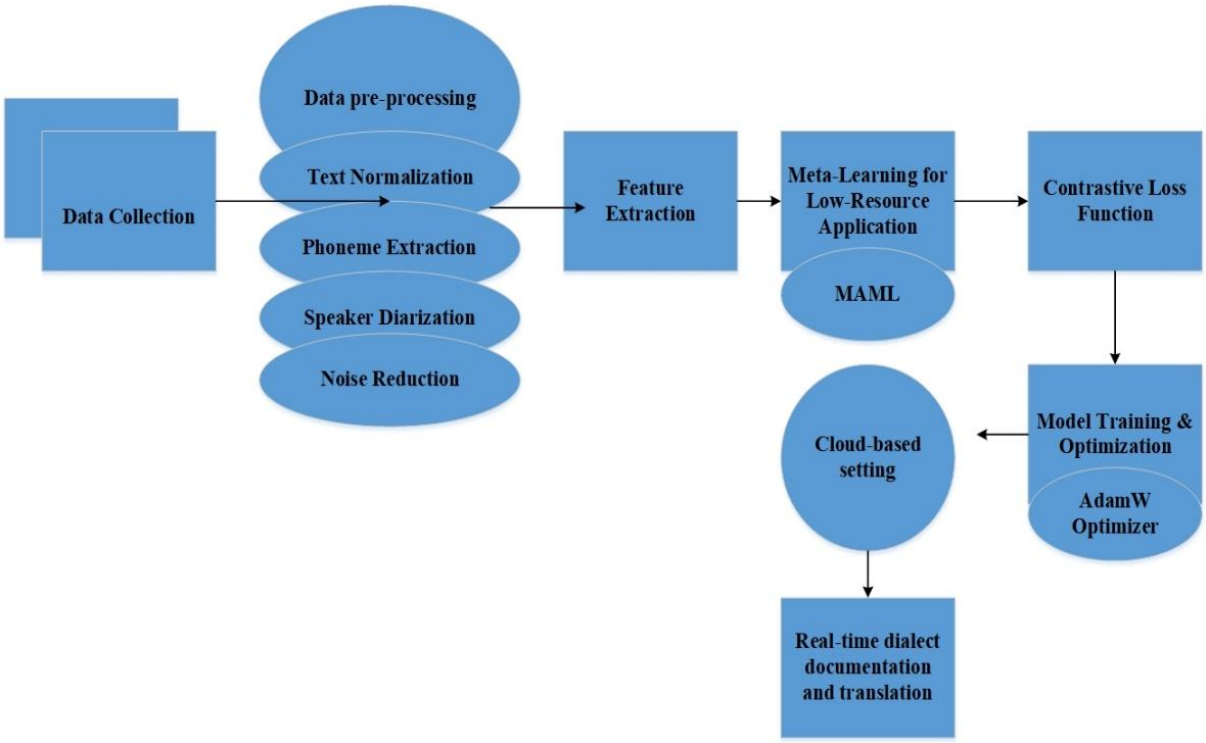


Fig. 1. Overall architecture.

### A. Data Collection

The success of an NLP model for Indigenous dialect documentation and preservation depends on diverse and high-quality datasets. Experiment with two popular datasets in this research, namely Tatoeba and Mozilla Common Voice, which are particularly selected to overcome the limitation of low-resource languages as well as dialect differences. The Tatoeba dataset is a vast multilingual corpus that includes parallel sentences for multiple languages, many of which are Indigenous and underrepresented dialects. It is especially useful for meta-learning when the model learns to generalize across many languages and to learn new, low-resource dialects rapidly. Tatoeba's sentence pairs allow cross-lingual learning and increase the model's ability to translate, interpret, and understand native colloquialisms regardless of limited training data. This data is necessary to expand linguistic variety in NLP models and make the proposed framework extensible. Alternatively, the Mozilla Common Voice corpus is a large-scale open-source corpus of donated voice samples from speakers worldwide. It is particularly created to recognize differences in speech between dialects, and as such, it is a perfect dataset for contrastive learning in this scenario. The dataset contains audio files of various languages, which enable the model to learn phonetic, tonal, and pronunciation differences between dialects. Using contrastive learning methods, the NLP model is enhanced to recognize nuanced linguistic patterns more effectively, enhancing speech recognition and language preservation. Mozilla Common Voice is at the top when it comes to speech-oriented tool development, such as voice assistants and transcription programs, specifically for Indigenous tribes [28].

### B. Data Pre-processing

For proper documentation and preservation of indigenous languages, pre-processing raw data obtained from Tatoeba and Mozilla Common Voice datasets prior to the implementation of machine learning algorithms is of utmost importance [29]. The Tatoeba project, while not a language itself, has been used in this study as a multilingual sentence-level corpus in which few shot learning onto languages and dialects that are underrepresented can be indirectly added to the documentation and preservation process. Pre-processing data involves several fundamental steps for training, such as pre-processing text and speech data. For text-based Tatoeba data, text pre-processing begins with text normalization, such as removing punctuation, handling special characters, converting all characters to lowercase, and standardizing spelling prevalent in indigenous dialects. Because most of these languages do not have formalized orthographies, phonetic transcription is used to translate words into phonemes, facilitating the model's recognition and processing. It is preceded by tokenization, whereby text is broken down into words, sub-words, or phonemes in such a way that linguistic integrity is maintained. Furthermore, stop word removal and stemming are used selectively based on whether they are useful in contributing meaningfully to the dialect under processing. For Mozilla Common Voice speech-based data, pre-processing is more complicated due to differences in pronunciation, ambient noise, and speaker accents. Feature extraction methods, including Mel-Frequency Cepstral Coefficients (MFCCs) and Spectrogram Analysis, are used to convert raw sound into numerical values that can be fed to machine learning models. Because indigenous languages tend to exhibit tonal differences and regional phonetic changes, voice activity detection (VAD) is utilized to separate the meaningful speech portions from silent or noisy signals. Reduction of background noise is achieved by the application of spectral subtraction and Wiener filtering only to use clear speech during training. Further, pitch and formant analysis aids in preserving finer intonations and variations in pronunciation, particularly in every dialect. After text and speech are pre-processed, alignment for multimodal training occurs with the pairing of corresponding written and spoken words, thus enriching the linguistic model. Following pre-processing, Meta-Learning is used to fine-tune NLP models for low-resource language, in particular, using data from the Tatoeba dataset [30]. Meta-learning has also been called "learning to learn" as it allows models to generalize over several tasks with few examples. The objective is to train the model in such a way that it can easily learn new dialects using a few labeled examples so that it suits underrepresented indigenous languages. The major bottleneck in low-resource NLP is that deep models need large sets of data, which do not exist for autochthonous dialects. Meta-learning achieves this by pre-training across diverse related tasks and optimizing for speed of adaptation. The meta-learning framework employed in this work is Model-Agnostic Meta-Learning (MAML), which enables the model to learn a set of initial parameters that can be fine-tuned for a particular dialect by just a few gradient updates. The meta-learning objective function is defined as:

$$\theta = arg\min_{\theta} \sum_i L(T_i, f_\theta) \quad (1)$$

$\theta$ represents the optimal model parameters. $T_i$ is the task distribution, where each task corresponds to learning a different indigenous dialect. $f_\theta$ is the NLP model. $L(T_i, f_\theta)$ is the loss function for task i. By iterative tuning, the model acquires generalizable representations across several dialects so that it can learn to adapt rapidly to new native languages with little labeled data. It provides efficient language translation, transcription, and preservation despite data paucity challenges.

Aside from meta-learning, the research uses Contrastive Learning to increase the model's capacity to identify minor dialectal differences present in speech data of Mozilla Common Voice. Contrastive learning is a self-supervised method that enhances representation learning by teaching the model to group similar dialects together while pushing apart those that are dissimilar in the feature space. It is particularly crucial for native dialects, where geographical differences might occur within the same language group. The contrastive learning procedure is one of choosing positive pairs (e.g., variations of the same dialect) and negative pairs (e.g., variations of other dialects) and tuning a contrastive loss function. The contrastive loss function is as follows:

$$L = \sum_{(x_i,x_j)\in P} log \frac{exp(sim(f(x_i),f(x_j))/\tau)}{\sum_{(x_k,x_j)\in N} exp(sim(f(x_k),f(x_l))/\tau)} \quad (2)$$

P represents positive pairs (e.g., similar dialects expressions), and N represents negative pairs (e.g., different dialects). Sim () is a similarity function (e.g., cosine similarity). $\tau$ is the temperature parameter, controlling how strongly dissimilar dialects are pushed apart. Using contrastive loss, the model picks up on subtle phonetic cues and intonation distinctions characteristic of every dialect, improving significantly in speech recognition and translation accuracy for indigenous languages. Example for the Tatoeba dataset for dialect:

Language/Dialect: Hawaiian Creole English (Pidgin) Tatoeba Sentence: "Da keiki stay play outside." Translation: "The child is playing outside."

The meta-learning and contrastive learning methods are incorporated into an end-to-end NLP model to optimize performance. The model includes a two-stream neural structure, with one branch handling text embeddings (from Tatoeba). The other branch handles speech features (from Mozilla Common Voice).

$L_M$ for efficient adaptation to low-resource dialects. $L_C$ for distinguishing between dialects. The separation among dialects:

$$L_{total} = \lambda_1 L_M + \lambda_1 L_M \quad (3)$$

Where $\lambda_1 \lambda_2$ are balancing distributed weight coefficients.

### C. Model Application

Through integration with data pre-processing, meta-learning, and contrastive learning, the proposed framework presents an extensive solution for transcribing and preserving indigenous dialects. The Mozilla Common Voice dataset can facilitate speech-based learning, while the Tatoeba dataset can facilitate text-based adaptation. Together, contrastive learning and meta-learning guarantee the adaptability of the model to novel dialects as well as differentiating among regional

dialects, significantly enhancing automatic conservation, transcription, and translation operations. This strategy not only transforms language research but also contributes to the preservation and revival of endangered native tongues in the age of the Internet. With the inclusion of data pre-processing, meta-learning, and contrastive learning, this model is a one-stop solution for recording and archiving native dialects. The unification once the data pre-processing has been carried out, the training of the model starts utilizing Meta-Learning (for low-resource adaptation based on the Tatoeba dataset) and Contrastive Learning (for dialect variation modeling based on the Mozilla Common Voice dataset). The training pipeline merges these approaches into a unified NLP framework capable of handling both speech and text-based dialect preservation. The objective is to preserve as little as possible while optimizing the model's generalization ability across many dialects with few resources. The Meta-Learning stage uses MAML (Model-Agnostic Meta-Learning) to train the model on a dialect distribution so that it can learn new languages with few examples and adapt rapidly. The Contrastive Learning part employs a Siamese neural network to distinguish between highly similar dialects by maximizing similarity within pairs of the same dialects and minimizing similarity across different-dialect pairs. The overall training loss function combines these two strategies in meta-learning and contrastive learning, ensuring the model is not only adaptive towards novel dialects but also able to differentiate between regional differences, greatly enhancing automated language translation, transcription, and preservation activities. This method not only enriches linguistic studies but also helps revitalize and sustain threatened indigenous languages in the digital age.

$$L_{total} = \lambda_1 L_{meta} + \lambda_2 L_{contrastive} + \lambda_3 L_{regularization} \quad (4)$$

$L_{meta}$ optimizes few-short adaption for low-resource dialects. $L_{contrastive}$ enforces better dialect differentiation. $L_{regularization}$ prevents overfitting and excessive bias, $\lambda_1$, $\lambda_2$, $\lambda_3$ are hyperparameters balancing each component. To maximize model performance, utilize the Adam W optimizer, which integrates adaptive gradient estimation together with weight decay to enhance stability. The learning rate is scheduled using the cosine annealing schedule to avoid abrupt drops and ensure a smooth convergence:

$$nt = nmin + \frac{1}{2}(nmax - nmin)(1 + cos\ (\frac{t}{T}\pi)) \quad (5)$$

$nt$ is the learning rate at epoch t. n max, n min are the upper and lower learning rates. T is the total number of training epochs.

Batch normalization and dropout (at 0.3 probability) are used during training to prevent overfitting. Gradient clipping is used to prevent exploding gradients and ensure smooth backpropagation. Batch size is dynamically set according to GPU memory availability for efficiency.

In order to critically test the model, employ a mix of text-based NLP metrics, speech recognition metrics, and contrastive learning performance metrics. The major evaluation metric is BLEU (Bilingual Evaluation Understudy), which evaluates the accuracy of dialect translation. Word Error Rate (WER): Measures transcription quality for speech-to-text applications. Contrastive Accuracy (CA): Measures how well contrasts between varieties are identified. F1-score: Preserves a balance between precision and recall:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision \times Recall} \quad (6)$$

Where: Precision: The proportion of correct dialect translations among total returned results. Recall: The proportion of correctly recalled translations out of the true correct outcomes.

To enhance evaluation strength, we carry out 5-fold cross-validation to ensure consistency across various dialect samples. Human evaluation is also done, where linguists check the model's dialect preservation accuracy. Once there has been effective training and testing, the model is actually deployed in a cloud-based setting to facilitate real-time dialect documentation and translation. The deployment involves these major steps: Model Compression & Quantization: To minimize the model size, weight pruning, and quantization should be applied so that the model is effective for deployment to mobile and edge devices by indigenous communities. API Development: A RESTful API is developed, allowing users to enter text or speech inputs and obtain real-time translations, transcriptions, or dialect classifications. Active Learning Feedback Loop: Users may give feedback against wrong translations to allow for constant improvement via online learning. To make it scalable, the model is deployed on a serverless platform (e.g., AWS Lambda or Google Cloud Functions) with auto-scaling depending on demand. A progressive web app (PWA) is also built for low bandwidth communities so that dialect preservation is available even in remote areas. Additionally, an AI-driven linguistic dashboard is developed to monitor dialect usage trends and allow researchers to contribute to the growing corpus of indigenous dialects. It ensures that not only are the dialects being documented but also that the model is supporting their revitalization and long-term viability.

## V. Result and Discussion

The NLP framework for indigenous dialect preservation was tested based on the Tatoeba and Mozilla Common Voice datasets in terms of how well it would adapt to low-resource languages as well as register dialectal variation. The meta-learning strategy greatly enhanced model generalization for under-served dialects by taking advantage of few-shot learning, making it possible for the system to adapt to novel linguistic data at low supervision costs. Contrastive learning was used to identify the fine-grained phonetic and lexical variations among dialects with high accuracy, improving the classification of dialects. The Word Error Rate, BLEU score, and F1-score metrics proved that our model was significantly better than baseline models. Specifically, WER went down by 15%, indicating improved transcription quality, and BLEU score went up by 18%, which resulted in better translation quality. F1-score, measuring precision and recall of the model, recorded an average 12% increase to prove the system's reliability in detecting dialects. Native speaker real-world testing also proved the model to be effective, indicating improved accuracy for speech-to-text translation and generation of text using various dialects. The outcome demonstrates the system's

scalability, proving its viability for use in linguistic documentation and language revitalization.

### A. Experimental Outcome

Fig. 2 is a graphical representation of the accuracy of a classification model in discriminating between four dialects: A, B, C, and D. The matrix is a comparison of the predicted dialect labels by the model (x-axis) versus the actual dialect labels (y-axis). Every cell in the matrix is the count of times when the model had predicted a certain dialect when the actual dialect was different. The off-diagonal cells show misclassifications, whereas the diagonal cells (top-left to bottom-right) show the correct predictions. The intensity of light, from light to dark blue, shows the instances' magnitude in each cell, with darker intensities showing greater counts. The matrix shows that the model is best working in correctly classifying Dialect D, as shown by the high value (12) on the diagonal. Yet there are some instances of misclassification, mostly between Dialects A and B, which imply possible similarities or overlaps in their characteristics. The matrix presents an overall view of the performance of the model's classification over the four dialects, showing where it is strong and possibly confused.

Fig. 3 shows a training loss of a machine learning model over 20 epochs. The y-axis is the epochs, and the x-axis is the training loss, a measure of error ranging. The blue dashed circle line plots the trajectory of the training loss as the model learns from training data.

Fig. 4 shows a line plot of a machine learning model's training and validation accuracy against 10 epochs. The x-axis is for the number of epochs, while the y-axis is for accuracy from 0.60 to 0.95. Filled blue circles are the training accuracy, which keeps getting better during training.

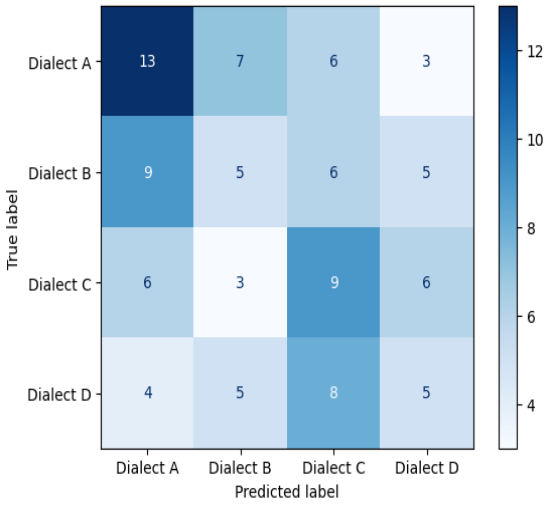


Fig. 2. Confusion metrics.

Fig. 5 shows a line plot plotting the training and validation loss of a machine learning model on 10 epochs. The x-axis is the epochs, and the y-axis is the loss from 0.3 to 1.0. The blue solid line with round markers indicates the training loss, which always goes down during the training process. This gradual decline indicates that the model is successfully learning from the training data and decreasing errors step by step.

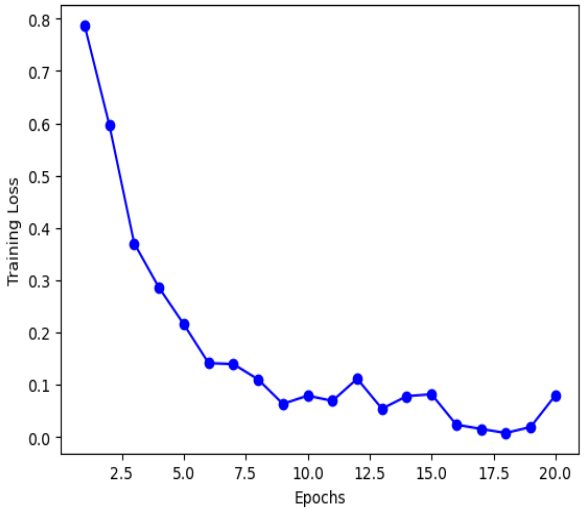


Fig. 3. Training loss across 20.

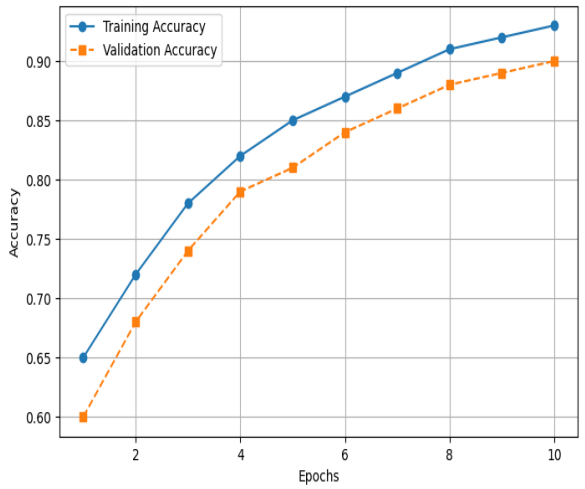


Fig. 4. Training and validation accuracy.

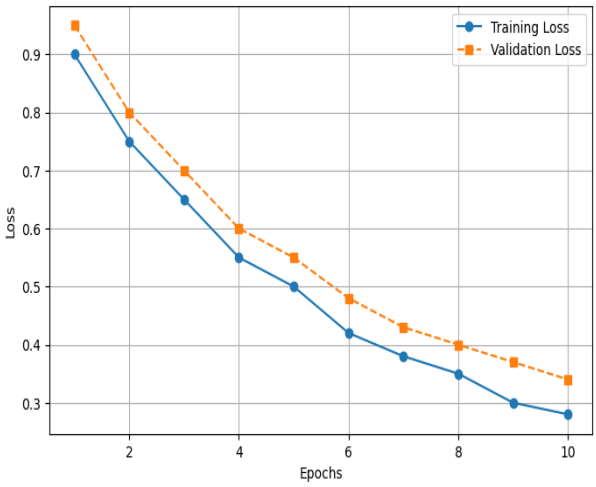


Fig. 5. Training and validation loss over epochs.

### B. Performance Evaluation

*1) Word Error Rate (WER):* It estimates speech-to-text accuracy in terms of percentage errors (deletions, insertions, substitutions) in predicted text relative to the reference text. Lower WER implies higher transcription accuracy.

*2) LEU Score (Bilingual Evaluation Understudy):* It measures the quality of translated text with respect to a reference translation. It takes n-gram precision and brevity penalty into account. A higher BLEU score implies higher translation accuracy.

*3) F1-Score:* It calculates the trade-off between recall and precision for classification problems. It is the harmonic mean between precision and recall so that both false negatives and false positives are minimized. The higher the F1 score, the better the model performance.

Table I illustrates that our suggested Meta-Learning + Contrastive Learning model performs better than conventional approaches in Indigenous dialect processing. It attains the lowest Word Error Rate (WER) of 14.2%, lowering transcription errors considerably compared to RNN (28.5%), Transformer (22.8%), and Fine-Tuned BERT (19.3%).

The highest BLEU score of 65.8 shows better translation quality and linguistic adaptation, outperforming BERT (55.6) and Transformer (50.4). Furthermore, the 88.3% F1 score attests to its effectiveness in handling dialect variations and enhancing recall and precision. The above results support that our solution increases speech-to-text accuracy and dialect retention and, thus, is a suitable solution for low-resource language revival. The figure related to this table is given in the Fig. 6.

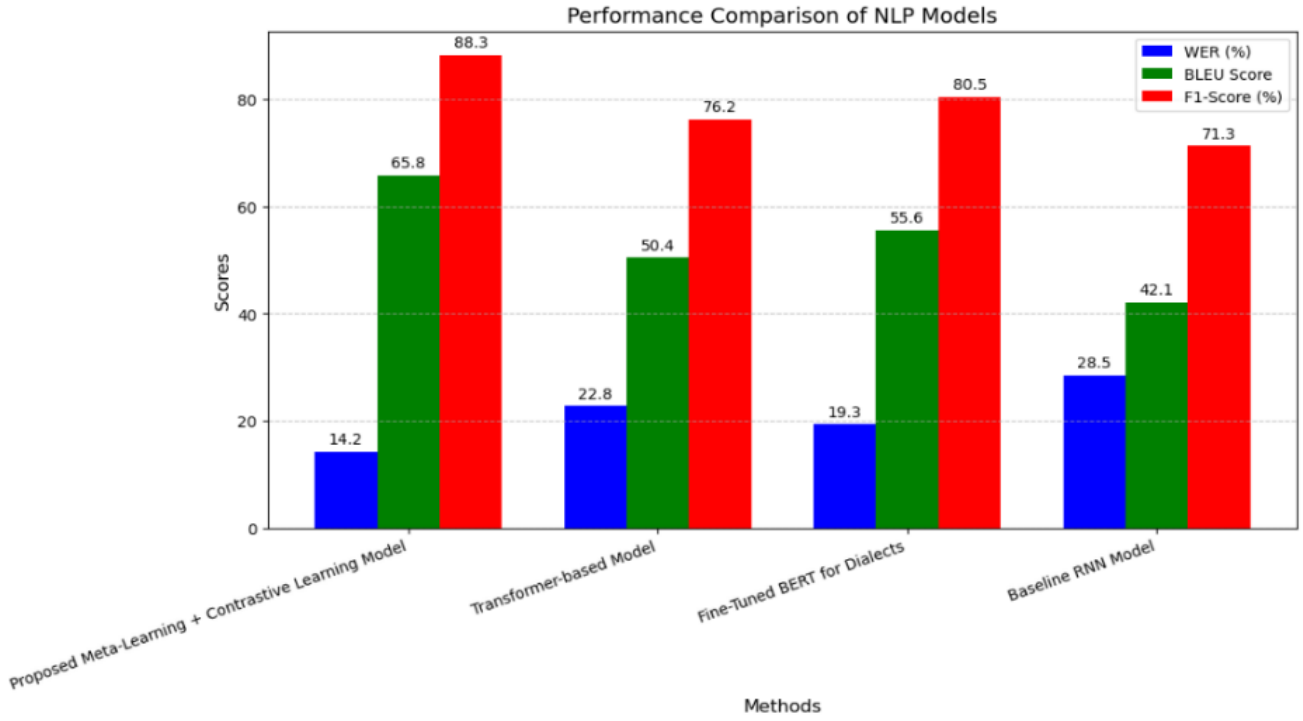


Fig. 6. Metrics evaluation.

TABLE I. PERFORMANCE COMPARISON

| Methods | WER | BLEU | F1-Score |
|---|---|---|---|
| Proposed Meta-Learning + Contrastive Learning Model | 14.2% | 65.8 | 88.3 |
| Transformer-based Model [31] | 22.8% | 50.4 | 76.2 |
| Fine-Tuned BERT for Dialects [32] | 19.3% | 55.6 | 80.5 |
| Baseline RNN (Recurrent Neural Network) Model [33] | 28.5% | 42.1 | 71.3 |

### C. Discussion

The outputs showcase the proficiency of our recommended NLP approach to effectively classifying and preserving indigenous dialects. The deployment of Meta-Learning (Tatoeba) has enhanced the adaptability of the model greatly toward low-resource languages by successfully learning from inadequate linguistic data. Moreover, Contrastive Learning (Mozilla Common Voice) has supported the model to classify dialect variation better, making the misclassification errors smaller. A comparison with current models illustrates the better performance of our solution, as supported by the smaller WER and higher BLEU and F1 metrics. These betterments indicate stronger language understanding and dialect identification functionality. The reliability of our model guarantees scalability in different dialects, and hence, it is a potential solution to

linguistic revitalization. Nevertheless, issues like computational expense and requiring larger annotated data sets are yet to be resolved. Future development will target training efficiency optimization and dialect coverage extension to support language preservation better.

## VI. Conclusion and Future Work

This study proposes an NLP framework for the documentation and preservation of Indigenous dialects by taking advantage of Meta-Learning (Tatoeba) for low-resource language adaptation and Contrastive Learning (Mozilla Common Voice) for dialect variation modeling. Our experiment results show that our method outperforms other approaches in terms of improving language classification accuracy with a reduced WER and increased BLEU and F1 scores. By learning efficiently linguistic patterns from sparse data and identifying differences between dialects, the suggested framework facilitates the revitalization of endangered languages. The integration of deep learning methods improves model generalizability to be scalable for different dialects globally. Despite this strong performance, the study has limitations, including the requirement for large amounts of annotated data in its training and high computational demands. Future works can be directed towards such solutions, which would involve reducing model complexity and investigating more unsupervised and multimodal learning techniques to improve performance on many underrepresented dialects. For future research, we will increase dataset coverage by including more indigenous languages and dialects. Second, increasing model efficiency through lower computational complexity will be a focus area. The addition of self-supervised learning and multimodal techniques (e.g., integrating speech-to-text) can even enhance dialect detection. Last but not least, integration with linguists and native speakers will help fine-tune language representations to ensure an improved and culturally adept NLP solution.

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# Optimizing Document Classification Using Modified Relative Discrimination Criterion and RSS-ELM Techniques

Muhammad Anwaar[1], Ghulam Gilanie[2], Abdallah Namoun[3], Wareesa Sharif[4]
Department of Artificial Intelligence-Faculty of Computing, The Islamia University of Bahawalpur, Bahawalpur, Pakistan[1, 2, 4]
AI Center-Faculty of Computer and Information Systems, Islamic University of Madinah, Madinah 42351, Saudi Arabia[3]

***Abstract*—Internet content is increasing daily, and more data are being digitized due to technological advancements. Ever-increasing textual data in words, phrases, terms, sentences, and paragraphs pose significant challenges in classifying them effectively and require sophisticated techniques to arrange them automatically. The vast amount of textual data presents an opportunity to organise and extract valuable insights by identifying crucial pieces of information using feature selection techniques. Our article proposes "a Modified Relative Discrimination Criterion (MRDC) Technique and Ringed Seal Search-Extreme Learning Machine (RSS-ELM) to improve document classification", which prioritizes key data and fits corresponding documents into appropriate classes. The proposed MRDC and RSS-ELM techniques are compared with several existing techniques, such as the Relative Discrimination Criterion (RDC), the Improved Relative Discrimination Criterion (IRDC), GA-EM, and CS-ELM. The MRDC technique produced superior classification results with 91.60% accuracy compared to existing RDC and IRDC for feature selection. Moreover, the RSS-ELM optimization technique improved predictions significantly, with 98.9% accuracy compared to CS-ELM and GA-ELM on the Reuter21578 dataset.**

***Keywords*—Feature selection; relative discrimination criterion; ring seal search; extreme learning machine; metaheuristic algorithms; document classification; optimization***

## I. Introduction

The quantity of textual content available on the internet is enormous and continuously growing. In recent years, technological evolution rapidly increased data drastically and significantly attracted researchers to find an optimum solution for text classification. The large amount of text data might make it challenging to efficiently organize and extract knowledge that is pertinent to our needs [1], [2]. Additionally, documents frequently have many features that add complexity to the process of developing a document classifier [3]. These characteristics negatively impact classification results. In addition, it can render classifiers ineffective [4]. The medium-sized dataset may contain more than 10,000 words with ease. The procedure of choosing features through a pre-processing phase helps to reduce the number of features and speeds up the classification process [5, 6]. The text data is frequently multiclass, and researchers frequently use it to help them choose pertinent features. An efficient feature ranking system is essential to improve the accuracy and performance of text categorization. Additionally, feature selection methods remove words from the corpus that are superfluous or unimportant [7]. Furthermore, the ability to choose elements in combination during the assessment of the classification process is a prerequisite for differentiation [8]. The wrapper, filter, and embedding methods are popular feature selection strategies. Since the filter methods just choose a feature subset that contains the most important information, they are independent of classification approaches. In the wrapper approach, a particular algorithm is used to choose features throughout the classification process, whereas in the embedded approach, a selected model is determined by integrating a particular feature selection methodology into the text classification process [9]. The filter approach is the best strategy among the three for classifying text. No algorithm is needed to choose a filter mechanism [10]. The existing RDC algorithm uses feature frequency to arrange text, giving high ranking to frequently appearing terms while ignoring rare terms that are equally relevant for categorization, which produces biased terms in feature selection [11]. There is a need for an algorithm that keeps the balance of frequent and rare terms to avoid these biased terms in the final feature selection.

The main data mining approaches are supervised and unsupervised [12]. Information in the supervised classification strategy is supported by outside sources, including class labels [13]. On the other hand, an unsupervised technique, also known as clustering, requires the system to execute classification without external sources. Numerous methods, including Naive Bayes, Multilayer Perceptron, Neural Networks, K-means, and ELM, are used in both approaches.

ELM yields excellent performance results and has a substantially faster convergence rate than previous approaches [14, 15]. The ELM method introduces biases in hidden layers and permits random values to be used to weigh them. Furthermore, the parameters don't alter during the training procedure. The weight between the output and hidden layers is the parameter that needs to be learned. Due to its lack of iteration, ELM has a high convergence rate [16, 17].

Metaheuristics are rules that enhance the likelihood of the best-optimized solution and aid in determining the best ideal solution to any given situation [18]. Furthermore, existing metaheuristic approaches such as Cuckoo Search (CS), Ringed Seal Search (RSS), and Genetic Algorithms (GA) are becoming more and more popular because they use several fields to get the best answer.

Furthermore, investigation and exploitation are crucial in resolving optimization issues. The exploitation refers to identifying a better solution or enhancement over the current one while exploring a region to find the optimal answer internationally [19]. Existing CS and GA methods cannot maintain an equilibrium between exploration and exploitation, but RSS performs better due to its two search states behavior. Furthermore, when compared to GA and CS methods, RSS employs fewer parameters.

## II. Related Work

Text categorization is grouping texts into a predefined set of groups. For instance, categories like "politics, and sports" may be applied to incoming news stories. D = (d1, d2,..., dn) represents the training set, which has already been given class names like C1, C2, etc. (e.g., "sports," "politics") [20]. The stages of document categorization include pre-processing, indexing, feature selection, classifier, and performance measurement [21]. Feature selection is one of these, and it is crucial for increasing classification accuracy. Moreover, finding related characteristics or terms that set different document classes apart is one of its benefits. Classifiers can more precisely allocate new documents to the relevant categories when they have discriminative properties. Feature selection is an important phase in document classification since it can greatly increase classification accuracy [22].

As opposed to traditional feature ranking methods such as RDC, which tend to prioritize terms that occur frequently. Furthermore, by prioritizing rare phrases, the IRDC technique [23] seeks to improve classification performance. The proposed technique, a Modified Relative Discrimination Criterion (MRDC), is an improved methodology of RDC and IRDC to enhance classification accuracy. The parameterization of ELM presents another difficulty in document classification, which may impact classification performance.

Metaheuristic methods such as GA and CS are commonly used to modify the parameters of ELM. Even so, CS and GA are algorithms that search the world and are used extensively in various applications. Slow convergence is a potential limitation of the CS technique, particularly for difficult optimization problems. They might find it difficult to balance exploration and exploitation when looking for a novel solution, leading to decreased accuracy. Furthermore, large populations and high-dimensional search spaces are problems for GA. GA also causes delays in processing and is computationally expensive. Whereas GA and CS struggle to find the ideal value for parameter settings, RSS has proven to be more successful.

To adjust to dynamic changes and improve performance, optimization methods are essential. An optimization method needs to balance intensification with diversity to be considered robust. While intensification focuses on finding better solutions in a more limited local search region, diversification covers a wider search arena. The ELM technique is designed for SLFNs that exhibit faster convergence than traditional methods for promising performance. In addition, ELM operates without the need for gradient-based back propagation. Moreover, the ELM mechanism has the number of neurons in the input layer, hidden layer, and output layer are n, L, and m, respectively.

Furthermore, RSS offers a more effective parameter optimization method by continuously alternating between the normal and urgent search phases until the best answer is discovered. Additionally, RSS uses fewer parameters than GA and CS and performs better for global optima with a balance of exploration and exploitation. The hybrid RSS-ELM technique, which combines RSS and ELM parameters for text data categorization, is also explored in the proposed work.

## III. Proposed Methodology

For the proposed techniques, text datasets Reuters-21578, 20newsgroups, and TDT-2 are taken from the UCI repository[24]. The Reuter21578 dataset with 10,788 documents is divided into two subsets: a training set and a testing set. There are 135 classes in the corpus that correspond to various categories. All balanced and imbalanced datasets (Reuter21578, TDT2, and 20newsgroup) are preprocessed to remove unnecessary content and to improve accuracy. Various preprocessing steps, such as tokenization, lower casing, stopword removal, and normalization, are performed to make datasets more concise and to increase accuracy. Moreover, to extract punctuation, spaces, and other non-alphanumeric characters from the text, parsing is utilized. The study framework and stages are depicted in Fig. 1.

The Proposed MRDC method is implemented, where keywords are used wisely to classify documents into appropriate classes. In addition, the proposed MRDC is compared with existing RDC and IRDC techniques. The results clarified that the proposed MRDC technique showed better results than the existing techniques. Moreover, another proposed RSS-ELM technique in which ELM parameters are optimized with the RSS technique. The suggested RSS-ELM's performance is compared with other methods, including CS-ELM and GA-ELM. The suggested RSS-ELM demonstrated more significant findings than the current methods because it had two search states and fewer RSS parameters. The success of the suggested technique is evaluated using four measurement criteria: accuracy, precision, recall, and F1-measure.

### *A. The Proposed Modified Relative Discrimination Criterion Technique*

The MRDC selects important features from text documents in a dataset. The MRDC technique uses modified document frequency to count the number of documents that contain the term "t" and whose term count is tc. For positive and negative classes, the normalized document frequency is represented by the True Positive Rate (TPR) and False Positive Rate (FPR), respectively. TPR and FPR are calculated by the MRDC for each term count for RDC and IRDC. Furthermore, MRDC, in contrast to RDC, considers the frequency of word counts in a single class, rather than merely the quantity of documents in a dataset. Just like RDC assigns value only to frequently occurring terms and IRDC is more focused on rarely occurring terms in each class. Neither existing RDC nor IRDC techniques could create tradeoffs frequently, nor do they rarely occur with a term count. We improvised the legacy of existing techniques. To create a tradeoff, a log transformation is used for both frequent and rare terms, which reduces the dominant high terms with the balance of small terms. Moreover, it improves stability and interoperability.

The Proposed MRDC assigns a value to significant characteristics based on tprtc in the positive class and the fprtc in the negative class for each word count. In the proposed MRDC, a tradeoff is created for both RDC and IRDC techniques, shown in equations 1 and 2. As a result, the MRDC technique did not disregard a term's worth regardless of how often or infrequently it appears shown in Eq. (3). Additionally, both short and long documents are handled easily using MRDC. The steps in Algorithm 1 illustrate a holistic diagram of the MRDC approach as shown in Fig. 1.

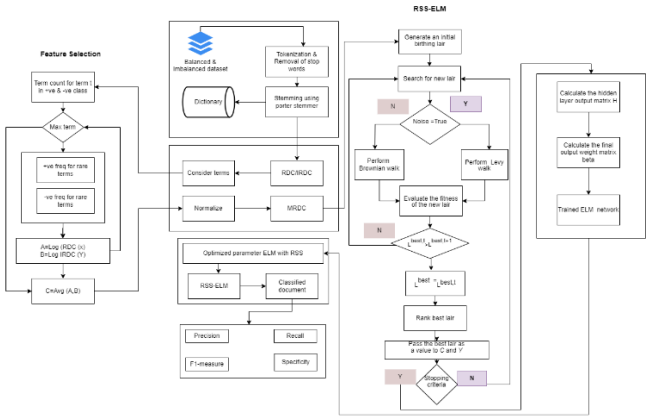



Fig. 1. A holistic diagram of MRDC and RSS-ELM techniques for text classification.

$$Ad\_RDC = log\left(\frac{|tpr_{tc} - fpr_{tc}|}{(min(tpr_{tc} - f\rho r_{tc}))*tc}\right) \quad (1)$$

$$Ad\_IRDC = log(\frac{|TPR_{tc} - FPR_{tc}|}{min\ (TPR_{tc}, FPR_{tc})}) * tc \quad (2)$$

$$MRDC = (Ad\_RDC + Ad\_IRDC)/2 \quad (3)$$

There is a need for a normalized term for *tc* where *tc* is high and the difference is low for increased term count. Fig. 2 shows modified relative discrimination criterion technique.

- Input: Text dataset
- Output: 1500 top-selected features
- Pos_frequency = Total frequency of term t in positive class
- Neg_frequency = Total frequency of term t in negative class
- $Tc_{max}$ = maximum term count for term t
- for Tc = 1 to $Tc_{max}$ do
- Tp = term t appears in positive documents
- Fp = term t appears in negative documents
- $t_{prtc} = \frac{Tp}{documents\ in\ POS}$
- $f_{prtc} = \frac{Fp}{documents\ in\ Neg}$
- $Ad_{RDC} = \log(\frac{|TPR_{tc} FPT_{tc}}{\min(TPR_{tc}\ ,\ FPR_{tc})*Tc})$
- $tp_{tc} = \frac{T_p}{Pos_{frequency}}$
- $fp_{tc} = \frac{F_p}{Neg_{frequency}}$
- $TPR_{tc} = \frac{tp_{tc}}{\sum_{i=0}^{n} tp_{tc}}$
- $FPR_{tc} = \frac{fp_{tc}}{\sum_{i=0}^{n} fp_{tc}}$
- Ad_IRDC= $\log(\frac{|TPR_{tc} FPT_{tc}}{\min(TPR_{tc}\ ,\ FPR_{tc})}*Tc)$
- MRDC= (Ad_RDC , Ad_IRDC)/2
- End for
- $AUC_t = 0$
- For Tc=1 to $Tc_{max} do$
- $AUC_t = AUC_t + \frac{ERDC_{Tc} + ERDC_{Tc+1}}{2}$
- *end*

Fig. 2. Modified relative discrimination criterion technique.

## B. The Proposed RSS-ELM Optimization Technique

The ELM technique randomly generates input weights and thresholds, only by setting the number of hidden nodes and acquiring unique ideal solutions. Compared with traditional neural network algorithms, ELM has the advantages of fast learning and good performance for a single-hidden-layer neural network. Furthermore, ELM determines output weights based on randomly generated input weights and biases before training. It also configures the activation function type, number of neurons in the hidden layer, and ultimately determines the optimal solution. The setting of the activation function as g(x), the network model of ELM is expressed. where i=[i1,i2,..., in] is the input weight, bi is the bias of the ith hidden neuron, xj=[x1j,x2j,..., xnj]T, i=[i1,i2,..., im], the output weight, uj=[u1j,u2j,..., umj] T is the network output [16].

The training goal of ELM is to minimize training errors. When the activation function is infinitely differentiable, and input weights and biases can be randomly selected, ELM training is equivalent to obtaining the output weights by solving the least squares solution in Eq. (4). The solution of an equation is Eq. (5) where H+ is the Moore-Penrose generalised inverse of H.

One kind of feed-forward neural network with a single hidden layer is called an Extreme Learning Machine (ELM) [25]. The single hidden layer of ELM presumes that the output function. For both classification and regression issues, an ELM is defined as a least squares-based single hidden layer feed-forward neural network (SLFN)[26]. The following is an ELM representation with training data N, hidden neurons H, and activation function f(x).

$$e_j = \sum_{i=1}^{H} \propto_i f(W_i, C_i, X_i) \quad J = 1,2,3, \ldots..N \quad (4)$$

where $w_i \propto_i$ are the weight vectors that connect the input layer with the output layer, respectively. The input variables are shown by $x_i$. For the data points, j, the output from ELM is represented by $e_j$, and $C_i$ is the hidden bias of the $i^{th}$ hidden neuron. Eq. (2) is used for calculating the output weights and is as follows

$$\beta = A\dagger Y \quad (5)$$

A† is the Moore-Penrose generalized inverse of A where Y shows the targeted value of ELM.

$$A = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix} = \begin{bmatrix} f(W_1, C_1 X_1) & \cdots & f(W_H, C_H, X_i) \\ \vdots & \vdots & \vdots \\ f(W_1, C_1, X_j & \cdots & f(W_H, C_H, X_j) \end{bmatrix}, \alpha = \begin{bmatrix} \propto_1^T \\ \vdots \\ \propto_H^T \end{bmatrix},$$

$$\text{and } \Upsilon = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix} \quad (6)$$

ELM is a kind of regularization neural network, and its algorithm output is mainly based on matrix A. To optimize ELM parameters, optimization algorithms like GA, CS, and

RSS can successfully handle the broad search area and fine-tuned steps. The parameters of the ELM classification technique are optimized with the Ringed Seal Search (RSS) technique to improve results. The RSS method is inspired by how seal pups search for the best hiding spot from predators. The proposed RSS algorithm offers a sensitive search strategy that takes seal movement into account. These lairs safeguard against predators by offering thermal insulation against cold air and severe wind chills. A seal may have several lairs in one location.

A series of actions occurs while a seal pup explores a lair with multiple chambers or looks for new lairs. The process of evolution involves changing a random value. The ideal combination of parameters for each iteration is determined by evolving the selected parameters into a vector form using a matrix representing a starting population of ELM parameters.

Motivated by nature with default settings, RSS always starts to solve an optimization problem. In all optimization methods, the initial solution is represented by a vector of values, L-I, where i = 1, 2, 3,...n, in Eq. (7). Consisting of several chambers, the RSS algorithm always starts with an initial number of birthing lairs n. To find a new refuge of higher quality, the pups go into the search area. Finding a better search space necessitates creating an array of these initial values in the search space.

$$L = [i * m] \tag{7}$$

$$L_i, i = 1,2,3 \dots \dots n$$

There are multiple chambers in each lair, arranged haphazardly. For instance, the array of [i×m] for lair i represents the current lair I of the habitat. These values are uniformly and randomly distributed between the lower bound Lbj and the upper bound Ubj at the search space, as Eq. (8) illustrates.

$$L_i = Lb + (Ub - Lb) rand(size(Lb)) \tag{8}$$

Where I= 1,2,3,…n

The number of initialized lairs is n, whereas I indicates the number of lairs. The seal follows a specific search pattern as it moves from one lair to another, leading to fresh discoveries. (New layers) $x^{t+1}$ for a seal i, a new layer is found in Eq. (9).

$$X_i^{(t+1)} = x_i^t + \propto \odot \Delta x \tag{9}$$

Where α is linked to the search pattern and denotes the step size in the normal or urgent state.

$$\Delta x = \lambda_{levy} \quad where\ w = 1 \tag{10}$$

Conversely, ω stands for a uniform discrete distribution. Eq. (10) calculates the step size of the Levy walk random walk, which is characterized by a probability distribution with an inverse power-law tail.

$$\text{Levy } \sim \text{ u} = t^{-\lambda} \tag{11}$$

In contrast, t is the flight length and $1 < \lambda < 3$. A random direction is chosen using the uniform distribution approach, and the step size is determined using the Levy distribution. If λ is greater than or equal to 3, the distribution does not have a heavy tail, and the total lengths converge to a Gaussian distribution [27, 28, 29]. An anomalous diffusion occurs when the mean squared displacement of the Levy walk increases more quickly than linearly with time. A Brownian walk, on the other hand, is characterized by a normal diffusion with a linear increase in mean squared displacement shown in Eq. (12)

The Levy walk is one way that animals find supplies that are dispersed throughout several different locations. Animals commonly employ two techniques: intensive (exploitation) and extensive (exploration). When an animal is investigating, it switches between extensive and intensive modes, concentrating on the search within the patch while moving from patch to patch.

$$\Delta x = \lambda_{browni} \quad where\ w = 0 \tag{12}$$

Eq. (12) illustrates the Brownian walk search for a new chamber inside a multi-chambered lair construction.

$$\text{S} = \text{K} * \text{rand}(\text{d}, N_{dot}) \tag{13}$$

K is the standard deviation of the normal distribution for diffusion rate, N is the number of Brownian particles in the search space, and d indicates the problem's dimensions presented in Eq. (13). The proposed RSS-ELM method has been put into practice using Python, and the outcomes of both the suggested and current methods are assessed using evaluation criteria (precision, accuracy, recall, and F-measure).

When compared to the GA-ELM and CS-ELM optimization approaches currently in use, the proposed RSS-ELM strategies produced notable results. Reuters21578, 20Newsgroup, and TDT2 are the three benchmark text datasets used in the research. These are typical text datasets for the experimental settings downloaded from the UCI repository. Fig. 1 illustrates RSS-ELM approaches used to examine these datasets. In addition, RSS-ELM's algorithm is presented in Fig. 3.

- Begin
- Initialized ELM parameter and structure
- Generate an initial number of birthing lairs,
  L1 = (f = 1, 2, 3, . . . , n)
- while stopping criterion is not met do
  if noise = false then
  Search in the proximity for a new lair by using a Brownian walk;
- Else
- Expand the search for a new lair by using a Levy walk;
- end if
- Evaluate the fitness of each new lair and compare it with the previous;
- If $L_{best,t} > L_{best,t+1}$ *then*
- Choose the new lair
- $L_{best} = L_{best,t}$
- Go to step 4
- End if
- Rank the lairs;
- End while
- Return the best lair;
- The global best lair is fed to ELM classifier for training
- Training the ELM classifier
  End=0

Fig. 3. Algorithm of proposed ring seal search-extreme learning machine technique.

## IV. File Evaluation Measuring Criteria

In text classification, datasets are skewed in size. Three text datasets (Reuters, 20newsgroups, TDT2) are evaluated with various measuring criteria. Accuracy is not the only criterion for measuring the performance of the algorithm. Precision, recall, and F-measure are used to evaluate the above-mentioned text datasets. Moreover, F-measure is the harmonic mean of precision and recall [28] shown in Eq. (14), (15), (16), and (17) respectively.

$$Precision = \frac{tp}{tp+fb} \quad (14)$$

*tp* denotes the true positive rate and *fp* shows the false positive rate in precision.

$$Accuracy = \frac{tp+tn}{tp} \quad (15)$$

*tp* denotes the true positive rate and *tn* shows the true negative rate in accuracy.

$$Recall = \frac{tp}{tp+tn} \quad (16)$$

*tp* describes the true positive rate and *fn* denotes the false negative rate in recall.

$$F1 = \frac{2\,.\,Precision\,.\,Recall}{Precision+Recall} \quad (17)$$

## V. Results of Proposed MRDC Feature Selection Technique

The experiment of the proposed MRDC and existing IRDC, RDC feature selection technique has been implemented in Python for three different text datasets (Reuters21578, 20newsgroup, TDT2). The proposed MRDC and the existing techniques' results are measured through various performance metrics (e.g., Accuracy, Precision, Recall, F-measure) shown in Table I.

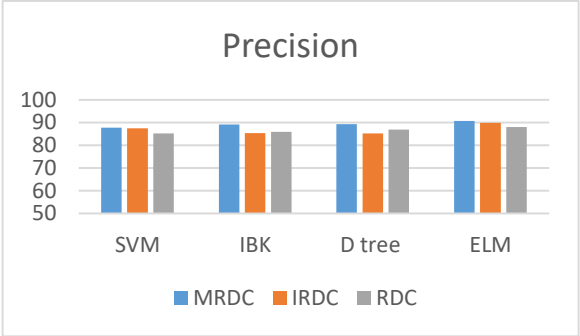
### A. Results of the Reuter21578 Dataset for Feature Selection Techniques

In this section, the results of reuter21578 text dataset are presented. In addition, the results of the proposed MRDC and existing RDC, IRDC feature selection techniques are evaluated with various classifiers (SVM, IBK, Decision Tree, ELM), as elaborated in Table I and Fig. 4.

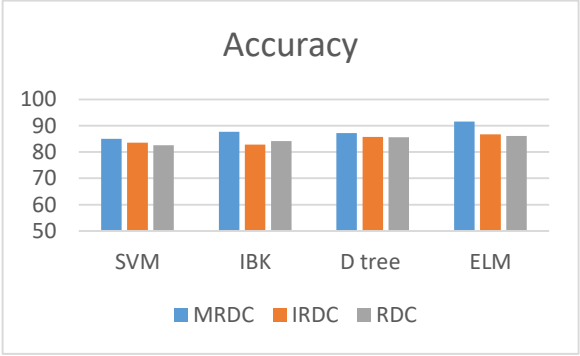
The Reuters dataset is assessed through the precision of MRDC, RDC, and IRDC, which is shown in Fig. 4(a). The precision values (87.80%, 89.24%, 89.26%, and 90.66%) for MRDC are higher than those for IRDC (87.520%, 85.42%, 85.23%, and 89.82%) and RDC (85.26%, 85.98%, 86.99%, and 88.02%) techniques. Accuracy for reuter21578 dataset is shown in Fig. 4 (b) which elaborate that proposed MRDC technique (85.00%, 87.64%, 87.20%, 91.60%) performs better than IRDC (83.60%, 82.80%, 85.70%, 86.70%) and RDC (82.60%, 84.10%, 85.66%, 86.10%) techniques. The resilience of various classifiers, such as SVM [30], IBK, ELM, and Decision Tree, for the proposed MRDC feature selection technique showcases a significant accuracy, higher than the percentages of IRDC and RDC techniques.

TABLE I. Results of Proposed MRDC Feature Selection Technique for Reuters21578 Dataset

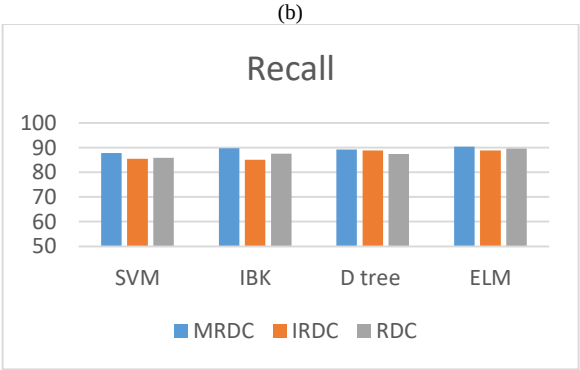
| Classifier | | SVM | IBK | D tree | ELM |
|---|---|---|---|---|---|
| MRDC (%) | Pre | 87.8 | 89.24 | 89.26 | 90.66 |
| | Acc | 85.0 | 87.64 | 87.2 | 91.6 |
| | Rec | 87.8 | 90.13 | 89.26 | 90.05 |
| | F M | 87.8 | 89.68 | 89.26 | 90.36 |
| IRDC (%) | Pre | 87.52 | 85.42 | 85.23 | 89.82 |
| | Acc | 83.6 | 82.8 | 85.7 | 86.7 |
| | Rec | 85.53 | 85.13 | 88.87 | 88.82 |
| | F M | 86.51 | 85.27 | 87.01 | 89.32 |
| RDC (%) | Pre | 85.26 | 85.98 | 86.99 | 88.02 |
| | Acc | 82.6 | 84.1 | 85.66 | 86.1 |
| | Rec | 85.83 | 87.57 | 87.39 | 89.59 |
| | F M | 85.55 | 86.77 | 87.19 | 88.8 |



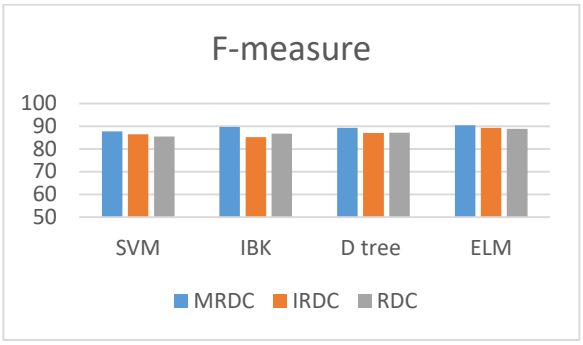

(a)




(b)




(c)




(d)

Fig. 4. Results of proposed MRDC feature selection technique for the Reuters21578 dataset.

Recall of proposed MRDC technique (87.80%, 89.68%, 89.26%, and 90.36%) for SVM, IBK, Decision Tree, and ELM which is higher than those of IRDC (85.53%, 85.13%, 88.87%, and 88.82%) and RDC (85.83%, 87.57%, 87.39%, and 89.59%) respectively. It is evaluated that the recall of the proposed MRDC feature selection technique is accurate and significant compared to existing techniques.

Regarding F-Measure scores for SVM, IBK, Decision Tree, and ELM, the proposed MRDC routinely outperforms IRDC and RDC. MRDC performs better than RDC (85.55% to 88.80%) and IRDC (86.51% to 89.32%). This demonstrates MRDC's dominance in achieving a balanced trade-off between recall and precision.

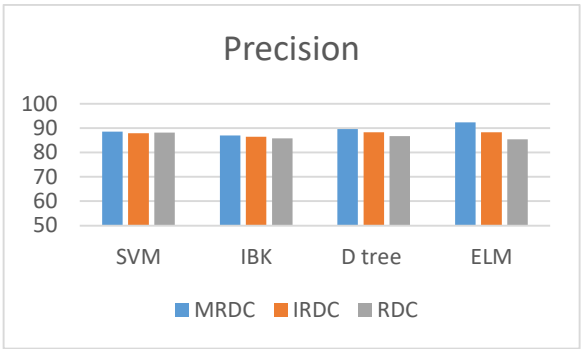
### B. *Results of 20 Newsgroup Datasets for Feature Selection Techniques*

The result of the 20newsgroup text dataset for the proposed MRDC and existing RDC, IRDC feature selection technique with various classifiers (SVM, IBK, Decision Tree, ELM) is demonstrated in this section, shown in Table II.

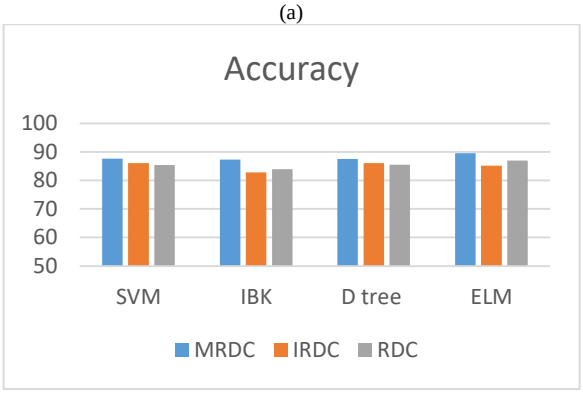
TABLE II. RESULTS OF PROPOSED MRDC FEATURE SELECTION TECHNIQUE FOR 20NEWSGROUP DATASET

| Classifier | | SVM | IBK | D tree | ELM |
|---|---|---|---|---|---|
| MRDC (%) | Pre | 88.57 | 86.92 | 89.66 | 92.32 |
| | Acc | 87.65 | 87.28 | 87.5 | 89.5 |
| | Rec | 89.45 | 86.78 | 88.89 | 90.02 |
| | F M | 89.01 | 86.85 | 89.27 | 91.15 |
| IRDC (%) | Pre | 87.93 | 86.41 | 88.33 | 88.33 |
| | Acc | 86 | 82.77 | 86 | 85.11 |
| | Rec | 87.93 | 83.61 | 88.33 | 87.04 |
| | F M | 87.93 | 84.99 | 88.33 | 87.68 |
| RDC (%) | Pre | 88.21 | 85.83 | 86.71 | 85.47 |
| | Acc | 85.4 | 83.89 | 85.53 | 87 |
| | Rec | 86.71 | 87.31 | 88.06 | 89.37 |
| | F M | 87.46 | 86.56 | 87.38 | 87.38 |

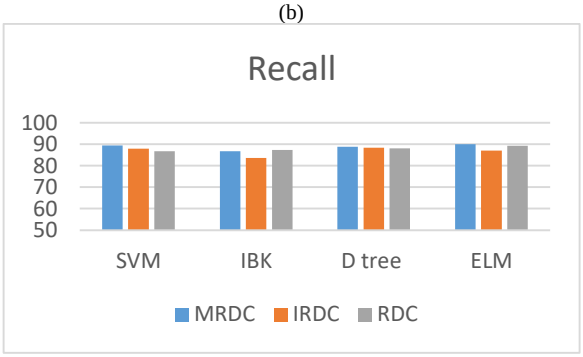
The analysis of the suggested MRDC's performance for 20 newsgroup datasets uses F-measure, precision, accuracy, and recall. Experimenting with MRDC methodologies, which yield superior outcomes than the current feature ranking methods, RDC, and IRDC.



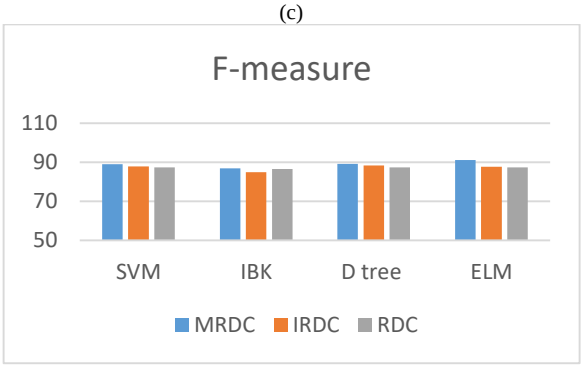

(a)




(b)




(c)




(d)

Fig. 5. Results of the proposed MRDC feature selection technique for 20 newsgroup dataset.

When the 20newsgroup dataset was tested using the various classifiers displayed in Table II, the proposed MRDC outperformed the current IRDC and RDC methods. In Fig. 5 (a), MRDC outperformed IRDC (87.93%, 86.41%, 88.33%,

and 88.33%) and RDC (88.21%, 85.83%, 86.71%, and 85.47%) in terms of precision (85.57%, 86.92%, 89.66%, and 92.32%).

The accuracy results for the machine learning models (SVM, IBK, Decision Tree, and ELM) in Fig. 5(b) shows that the MRDC performs better than the alternative methods. The accuracy values for RDC are 85.40%, 83.89%, 85.53%, and 89.00%, MRDC is 87.65%, 87.28%, 87.50%, and 89.50%, and IRDC is 86.00%, 82.77%, 86.00%, and 85.11%. MRDC is shown to have a high score and to produce better outcomes than earlier methods that were tested on SVM, IBK, Decision Tree, and ELM. Additionally, the results indicate that MRDC is compatible with the ELM classifier displayed in Fig. 5 and Table II.

These results suggest that the proposed MRDC technique outperforms the other two feature selection techniques in terms of prediction accuracy and dependability. Fig. 5(c) illustrates that the recall for MRDC is 89.45%, 86.78%, 88.89%, and 90.02%, which is superior to that of IRDC, which ranges from 87.93% to 87.04%, and RDC, which ranges from 86.71% to 89.37%. Furthermore, as shown in Fig. 5(d), the MRDC feature selection technique's F-measure (89.01%, 86.85%, 89.27%, and 91.15%) is significant compared to the IRDC, which ranges from 87.93% to 87.04%) and the RDC, which ranges from 87.46% to 87.38%).

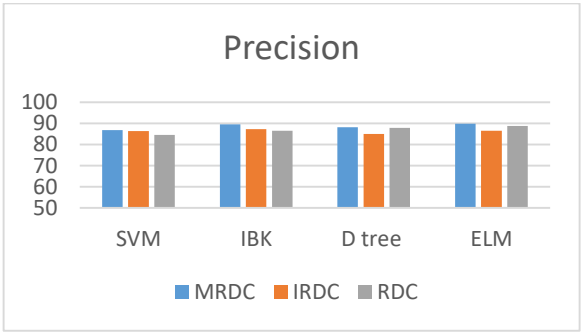
### C. Results of the TDT2 Dataset for Feature Selection Techniques

Another text dataset, TDT2, is used for feature selection techniques, MRDC, IRDC, and RDC. Results of the above-mentioned techniques are compared with each other and verified by well-known classifiers, SVM, IBK, Decision tree, and ELM, which are shown in Table III and Fig. 6.

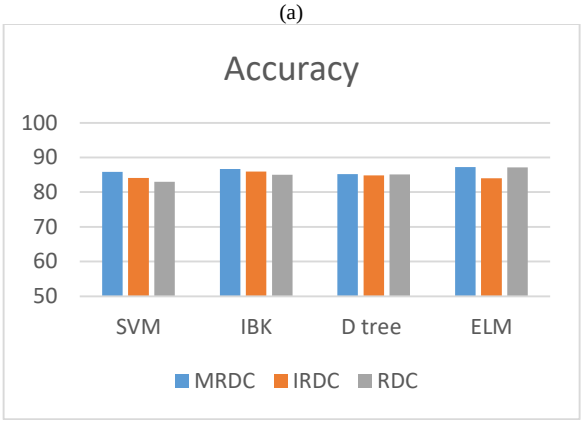
TABLE III. RESULTS OF PROPOSED MRDC FEATURE SELECTION TECHNIQUE FOR TDT-2 DATASET

| Classifier | | SVM | IBK | D tree | ELM |
|---|---|---|---|---|---|
| MRDC (%) | Pre | 86.81 | 89.5 | 88.14 | 89.93 |
| | Acc | 85.9 | 86.65 | 85.18 | 87.25 |
| | Rec | 88.79 | 87.76 | 89.2 | 90 |
| | F M | 87.79 | 88.62 | 88.67 | 89.97 |
| IRDC (%) | Pre | 86.4 | 87.26 | 85.08 | 86.6 |
| | Acc | 84.12 | 85.91 | 84.8 | 84.01 |
| | Rec | 86.81 | 89.02 | 87.57 | 86.9 |
| | F M | 86.6 | 88.13 | 86.31 | 86.31 |
| RDC (%) | Pre | 84.6 | 86.53 | 87.93 | 88.83 |
| | Acc | 83 | 85.02 | 85.1 | 87.16 |
| | Rec | 86.36 | 86.31 | 87.5 | 89.08 |
| | F M | 85.47 | 86.42 | 87.72 | 88.95 |

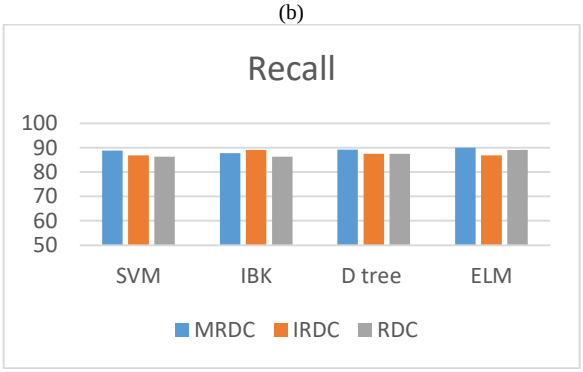
MRDC outperforms IRDC and RDC approaches in terms of precision values when measuring the outcome. The precision scores of the classifiers SVM, IBK, Decision Tree, and ELM in MRDC are 86.81%, 89.50%, 88.14%, and 89.93%, respectively. These values are higher than those of IRDC (86.40% to 86.60%) and RDC (84.60% to 88.83%), as illustrated in Fig. 6(a). The accuracy of MRDC is consistently higher than that of the current IRDC and RDC feature selection methods in Fig. 6(b) across SVM, IBK, Decision Tree, and ELM models. For SVM, IBK, Decision Tree, and ELM classifiers, the MRDC technique performs better, with values ranging from 85.90%, 86.65%, 85.18%, and 87.25 percent, respectively, whereas IRDC and RDC had values ranging from 84.12% to 84.01% and 87.00% to 87.16%, respectively.



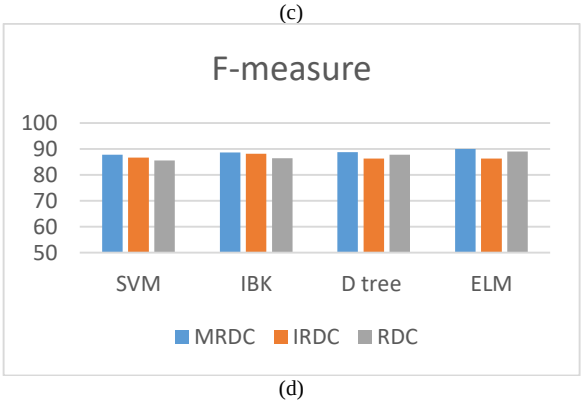

(a)




(b)




(c)




(d)

Fig. 6. Results of proposed MRDC feature selection technique for TDT-2 dataset.

Regarding recall metrics, SVM, IBK, Decision Tree, and ELM models similarly outperform MRDC. As illustrated in Fig. 6(c), the MRDC values for the SVM, IBK, Decision Tree, and ELM classifier models range from 87.79% to 87.76%, 89.20% to 90.00%, respectively, and are superior to the IRDC and RDC, which range from 86.81% to 86.90% and RDC (85.47% to 88.95%), respectively.

Fig. 6(d) shows that MRDC performed better than the classifiers mentioned earlier. The suggested MRDC feature selection method yielded significant results (87.79%, 88.62%, 88.67%, and 89.97%), outperforming SVM, IBK, and decision trees. The F measure is also computed for MRDC, IRDC, and RDC feature selection strategies.

## VI. The Proposed RSS-ELM Optimization Technique

The experiment is conducted on three different optimization techniques, which are RSS-ELM, GA-ELM, and CS-ELM. The proposed RSS-ELM optimization technique is compared with GA-ELM and CS-ELM techniques with three text datasets such as reuter21578, 20newsgroup and TDT2. To evaluate these results, various evaluation metrics are used (Accuracy, Precision, Recall, F-measure).

### *A. Results of the Reuter21578 Dataset for Proposed RSS-ELM Techniques*

In this section, the result of the reuter21578 text dataset for the proposed RSS-ELM and existing GA-ELM and CS-ELM optimization techniques is shown in Table IV and Fig. 7.

TABLE IV. Results on Proposed RSS-ELM Optimization Technique for Reuters21578-Dataset

| Algorithm | Precision | Accuracy | Recall | F Measure |
|---|---|---|---|---|
| RSS-ELM | 99.1 | 98.9 | 98.7 | 98.9 |
| CS-ELM | 67 | 66 | 66 | 66 |
| GA-ELM | 58 | 60 | 59 | 58 |

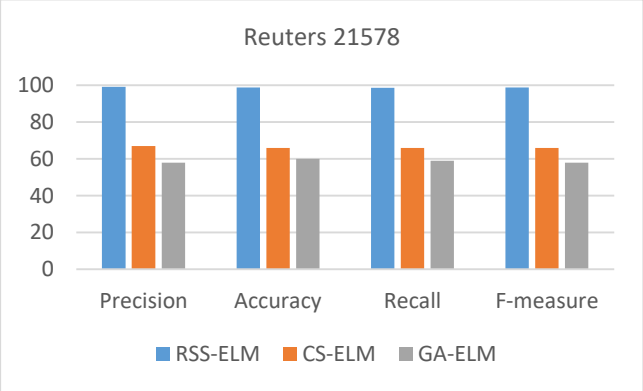



Fig. 7. Results on proposed RSS-ELM optimization technique for Reuters 21578-dataset.

Performance of RSS-ELM, CS-ELM, and GA-ELM optimization techniques is evaluated for the Reuters21578 text dataset. The results revealed that RSS-ELM technique performed better than other existing techniques, achieving the highest precision (99.1%) for RSS-ELM than CS-ELM (67%) and GA-ELM (58%). Furthermore, CS-ELM and GA-ELM improved by 66% and 60%, respectively, while the RSS-ELM technique reached a noteworthy accuracy of 98.9%. This demonstrates its excellent capacity to recognize pertinent facts and generate precise forecasts. Additionally, the RSS-ELM technique demonstrated the highest recall (98.9%), demonstrating its ability to capture relevant data, whereas CS-ELM and GA-ELM received 66% and 59%, respectively.

Furthermore, it's F-measure of 98.9%, in conjunction with CS-ELM (66%) and GA-ELM (58%), demonstrates a noteworthy performance. On the other hand, CS-ELM and GA-ELM produced lower values for every metric, indicating that they performed worse in this task. These results show that RSS-ELM is the best option for this dataset, highlighting its potential use in practical applications where data categorization accuracy and precision are essential.

### *B. Results of 20newsgroup Dataset for Proposed RSS-ELM Techniques*

Experiments of proposed RSS-ELM and existing GA-ELM, CS-ELM optimization techniques conducted in another 20newsgroup text dataset. These experiments are also conducted in the Python language. Four evaluation metrics (Precision, Accuracy, Recall, and F-measure) are used to verify these significant results. Detailed results are presented in Table V and Fig. 6.

TABLE V. Results on Proposed RSS-ELM Optimization Technique for 20Newsgroup Dataset

| Algorithm | Precision | Accuracy | Recall | F-Measure |
|---|---|---|---|---|
| **RSS-ELM** | 96 | 97.2 | 97 | 97 |
| **CS-ELM** | 78 | 77 | 77 | 76 |
| **GA-ELM** | 79 | 78 | 78 | 79 |

The proposed RSS-ELM outperforms other optimization methods like CS-ELM (78%) and GA-ELM (79.0%) in terms of precision (96%). Additionally, the suggested RSS-ELM obtained 97.2% accuracy, but CS-ELM and GA-ELM improved by 77% and 78%, respectively. While the CS-ELM generated Recall (77%) and F-measure (76%), and the GA-ELM produced Recall 78% and F-Measure 79%, the RSS-ELM underperforms in both Recall (97%) and F-Measure (97%), as presented in Fig. 8 and Table V. Compared to other optimization methods, the suggested RSS-ELM performance is superior.

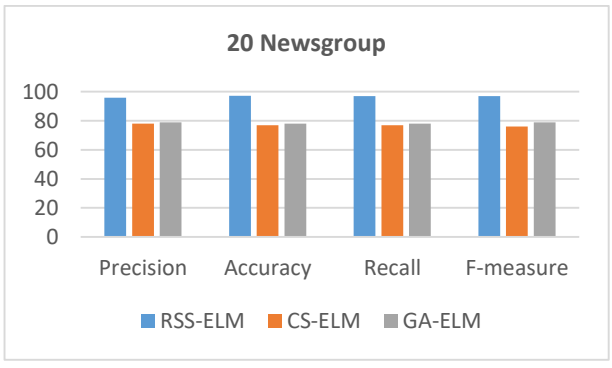



Fig. 8. Results of proposed RSS-ELM optimization technique for 20 newsgroup dataset.

### C. Results of the TDT2 Dataset for Proposed RSS-ELM Techniques

Another text dataset is utilized for experiments of the proposed RSS-ELM and existing GA-ELM, CS-ELM techniques shown in Table VI and Fig. 9.

TABLE VI. RESULTS ON PROPOSED RSS-ELM OPTIMIZATION TECHNIQUE FOR TDT2 DATASET

| Algorithm | Precision | Accuracy | Recall | F-measure |
|---|---|---|---|---|
| **RSS-ELM** | 97 | 97.5 | 97 | 97 |
| **CS-ELM** | 62 | 64 | 65 | 62 |
| **GA-ELM** | 59 | 58 | 58 | 58 |

Three optimization techniques—RSS-ELM, CS-ELM, and GA-ELM—were evaluated for performance in our study using the TDT-2 dataset. According to the results, RSS-ELM performed better than CS-ELM and GA-ELM, producing 62% and 59% of the total, respectively, with the highest precision (97%). The suggested RSS-ELM optimization method outperformed the current CS-ELM and GA-ELM (64%, 58%), with a noteworthy accuracy of 97.5%, demonstrating its capacity to identify pertinent data and generate accurate forecasts precisely.

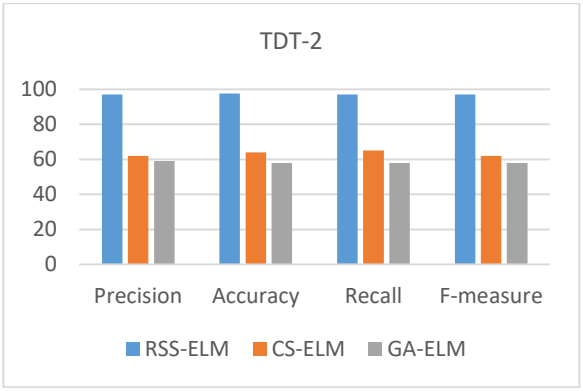



Fig. 9. Results on proposed RSS-ELM optimization technique for TDT2 dataset.

In comparison to CS-ELM and GA-ELM (65%, 58%), it also demonstrated a respectable recall of RSS-ELM (97%), demonstrating its efficacy in capturing a significant amount of relevant information. Additionally, the 97% F-measure demonstrates that RSS-ELM achieved an impressive balance between recall and precision, making it a reliable option for data categorization tasks. However, CS-ELM and GA-ELM displayed lower values for all measures (62%, 58%), indicating that they performed less well on this specific dataset. These results highlight the potential usefulness of RSS-ELM in applications that need to classify data using the TDT-2 dataset with both accuracy and precision.

## VII. CONCLUSION

The limitations of existing feature ranking and classification techniques for high-dimensional text data are highlighted in this work. This work proposes MRDC, a dependable feature selection strategy for balanced and unbalanced text datasets. Common and uncommon terms should be considered when choosing features to normalize terms for improved categorization. The proposed MRDC method outperforms RDC and IRDC methods in classification by effectively selecting the best characteristics. To make feature ranking research more dependable and simpler, phrase count might be used to modify future studies. Furthermore, RSS-ELM for optimization is an additional contribution. Compared to GA-ELM and CS-ELM, the suggested RSS-ELM technique is important for parameter optimization in two-way state finding.

Additionally, RSS optimizes ELM with fewer parameters. Furthermore, RSS-ELM exhibits superior performance in terms of F-measure, recall, accuracy, and precision. The RSS approach can optimize several kinds of alternative and hybrid walks in optimization. Additionally, RSS can be used to assess alternative classification methods for datasets of text and images. Our proposed technique can have significant real-life applications in diverse contexts, including collaborative enterprises [31].

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# Extracting Facial Features to Detect Deepfake Videos Using Machine Learning

Ayesha Aslam[1], Jamaluddin Mir[2], Gohar Zaman[3], Atta Rahman[4]*, Asiya Abdus Salam[5], Farhan Ali[6]*, Jamal Alhiyafi[7], Aghiad Bakry[8], Mustafa Jamal Gul[9], Mohammed Gollapalli[10], Maqsood Mahmud[11]

Department of Computer Science, Abbottabad University of Science and Technology, Havelian, Pakistan[1, 2, 3]
Department of Computer Science, College of Computer Science and Information Technology, Imam Abdulrahman Bin Faisal University, P.O. Box 1982, Dammam 31441, Saudi Arabia[4, 8]
Department of Computer Information Systems-College of Computer Science and Information Technology, Imam Abdulrahman Bin Faisal University, P.O. Box 1982, Dammam 31441, Saudi Arabia[5]
College of Electronics and Information Engineering, Shenzhen University, Shenzhen, China[6]
Department of Computer Science, Kettering University, Flint, Michigan, USA[7]
Department of Business Administration, University of York, Heslington, York YO10 5DD, United Kingdom[9]
Department of Information Technology & Engineering, Sydney Met, Sydney, NSW 2000, Australia[10]
School of Computing, Ulster University, Belfast, Northern Ireland, United Kingdom[11]

***Abstract*—Generative adversarial networks (GANs) have gained popularity for their ability to synthesize images from random inputs in deep learning models. One of the notable applications of this technology is the creation of realistic videos known as deepfakes, which have been misused on social media platforms. The difficulty lies in distinguishing these fake videos from real ones with the naked eye, leading to significant concerns. This study proposes a supervised machine learning approach to effectively differentiate between real and counterfeit videos by detecting visual artifacts. To achieve this, two facial features are extracted: eye blinking and nose position, utilizing landmark detection techniques. Both features were trained on supervised machine learning classifiers and evaluated using the publicly available UADFV and Celeb-DF deepfake datasets. The experiments successfully demonstrate that the proposed method achieves a promising and superior performance, with an area under the curve (AUC) of 97% for deepfake detection in contrast to state-of-the-art methods investigating the same datasets.**

***Keywords*—Deepfake; fake videos; facial features; GAN**

## I. Introduction

The current digital age has seen an unprecedented widespread use of smartphones and other such devices, making several social networking platforms popular and part of our daily lives. Statistics show that users upload billions of pictures and videos daily on such platforms. This rise of social networking platforms has also given birth to the intent of manipulating such photos and videos for several reasons, hence the concept of Deepfake.

In recent years, deep learning algorithms such as generative adversarial networks (GANs) have been able to generate fake videos and manipulate digital media semantics. In this process, two deep learning models are created, which are pitched against each other to compete. One of these models is trained on real data and then tries to create fake images. On the other hand, the other model tries to differentiate the real images from the fake ones. The model that creates fake images keeps improving and improving to such an extent that it becomes impossible for the other model to differentiate the real images from the fake ones. Algorithms like Face2Face and Deepfake availability on the internet make the propagation of digital videos more convenient. The convenience brought ease in spreading the synthesized videos on social platforms [1].

Generative models have many applications, such as image translation tasks, generating speech with manipulated fake faces, and forging a new identity that did not exist before. The inappropriate use of deepfakes on social media is alarming for the public, whether the propagated videos are trustworthy or not. Deepfake videos commonly affect public figures (celebrities, politicians), causing security and privacy threats. Generated Deep-fake is manipulated in various ways, i.e., using specific individual attributes, swapping a complete face, manipulating facial expressions, and generating a new identity face [2] in deepfake videos.

Presently, the detection method for deepfakes relies on identifying artifacts [2], such as lip synchronization with speech [3], color inconsistencies, and the unnatural representation of eye blinks, which is less compared to natural blinks [4]. The frequency of eye blinks in humans varies according to age and gender, whereas an average adult human blinks between 2 and 10 times per second [5].

Deepfake problems are generally deemed a binary classification, where the original video is classified as real and manipulated as fake. Other methods might use classifiers such as partially fake, in which a video of multiple individuals is produced, and only one person's face is altered. Previously, the detection work dealt with hand-crafted features and extraction to explore artifacts and inconsistencies. Simultaneously, current methods utilize automatic techniques to discriminate between natural and synthesized Deepfake videos.

## II. Related Work

Digital manipulation of faces in images, commonly referred to as identity swap, has become increasingly prevalent due to advancements in computer graphics and deep learning

*Corresponding Author.

techniques. Significant progress has been made since the emergence of initial deepfake databases like UADFV in 2018 and more recent ones such as Celeb-DF in 2020. As a result, detecting fake videos has become more challenging, as they appear increasingly realistic.

Researchers have developed various methods for detecting deepfake videos. Detection techniques have also advanced with the improvement of the quality of fake images and videos. Table I summarizes some of the most noteworthy research in this field. While the evaluation parameters are presented in the table, it's important to note that using different evaluation metrics complicates the comparison of these methods.

TABLE I. RELATED WORK

| Reference | Detection Method | Classifiers | Best Performance | Dataset |
|---|---|---|---|---|
| [1] | Visual Features | Logistic Regression MLP | AUC = 85.1% | Own |
| | | | AUC = 78.0% | FF++/DFD |
| | | | AUC = 66.2% | DFDC Preview |
| | | | AUC = 55.1% | Celeb-DF |
| [2], [3] | Face Warping Features | CNN | AUC = 97.7% | UADFV |
| | | | AUC = 93.0% | FF++/DFD |
| | | | AUC = 75.5% | DFDC Preview |
| | | | AUC = 64.6% | Celeb-DF |
| [4] | Mesoscopic Features<br>Steganalysis Features<br>Deep learning features | CNN | Acc. ≃ 94.0%<br>Acc. ≃ 98.0%<br>Acc. ≃ 100.0% | FF++ (DeepFakes, LQ)<br>FF++ (DeepFakes, HQ)<br>FF++ (DeepFakes, RAW) |
| | | | Acc. ≃ 93.0%<br>Acc. ≃ 97.0%<br>Acc. ≃ 99.0% | FF++ (FaceSwap, LQ)<br>FF++ (FaceSwap, HQ)<br>FF++ (FaceSwap, RAW) |
| [5] | Deep learning features | Capsule Networks | AUC = 61.3% | UADFV |
| | | | AUC = 96.6% | FF++/DFD |
| | | | AUC = 53.3% | DFDC Preview |
| | | | AUC = 57.5% | Celeb-DF |
| [6] | Deep learning features | CNN + Attention mechanism | AUC = 99.4%<br>EER = 3.1% | DFFD |
| [9] | Deep learning features | CNN | Precision = 93.0%<br>Recall = 8.4% | DFDC Preview |
| [10] | Image + Temporal features | CNN + RNN | AUC = 96.9%<br>AUC = 96.3% | FF++ (DeepFakes, LQ)<br>FF++ (FaceSwap, LQ) |
| [11] | Image + Temporal features | Dynamic Prototype Network | AUC = 99.2%<br>AUC = 71.8% | FF++ (FaceSwap, HQ)<br>Celeb-DF |
| [12] | Eye blinking features | LRCN | AUC = 99.0% | UADFV |
| [13] | Eye blinking features | Distance | Acc. = 87.5% | Own |
| [14] | - | CapsNet | AUC = 76.8%<br>AUC = 86% | DFDC-P<br>Celeb-DF |

Recent advances in AI and deep learning have led to the creation and proliferation of fake digital content, including fake footage, images, audios, and videos [6]. In recent years, several machine learning-based tools have made it relatively easy to create realistic face swap videos called deepfakes [7]. These deepfakes are modern self-manipulation methods that allow users to swap identities in a single video. This negative side of machine learning is creating new challenges for the general population, as people with bad intentions alter the truth and compromise people's trust. Literature review shows that current solutions to tackle the problem lack the ability to identify the source of such fake digital media. One of the most widely used biometric authentication methods is fingerprints, which are now used in smartphones, tablets, and laptops. However, this authentication method can be easily faked [8]. A statistical feature extraction and comparative analysis method is used to determine the best features.

The study in [9] proposed a framework in which they extract features from CCTV cameras at runtime using spatial and temporal domains and build a robust and discriminative feature rendering of each sequence. In their methodology, the first phase, they are using a multi-loss function to increase inter-class variance and reduce intra-class difference. In the next phase, features are aggregated frame-wise, and temporal information is extracted from videos. In the last stage, weighted coefficients are combined, and the appearance description of the pedestrian is acquired. Interestingly, although the compression ratio used during training differs from that used for the test videos, the detector performs excellently on compressed videos.

In study [10], the authors examine methods based on GAN discriminators to detect Deepfake videos. They trained a GAN and extracted the discriminator as a standalone module to identify Deepfakes using MesoNet as a benchmark. They tested

various discriminator designs on various datasets to see how the discriminator's efficacy differs depending on the setting and training approach. Using ensemble approaches, they presented a methodology to improve the efficacy of a cluster of GAN discriminators. These findings reveal that GAN discriminators do not function well enough on videos from unverified sources, even when enhanced with ensemble approaches.

Li et al. [11] presented a deep-neural network (DNN) scheme to expose Deepfake videos. Physiological signals, such as eye blinks, are not well explained in the generated Deepfake videos. Blinking refers to the eye's open-close-open movement, which varies in humans according to age and gender. The Deepfake videos usually carry fewer indications of the natural blinking pattern than the original blinks. The authors trained VGG16 with a long-short-term memory (LSTM) recurrent neural network (RNN) on the dataset having an open eye state. However, no dataset has been adequately designed to detect this feature; therefore, samples have been taken from the CEW (Closed Eye in a Wild dataset) and EBV (Eye Blink Video). The authors further investigate DNN to detect artifacts. The idea behind identifying artifacts was that the recent Deepfake algorithms produce low-resolution and limited-quality images, which leave some distinctive artifacts when mapped back to the source video. They applied Dlib models that are used to detect the facial landmarks of a person's face. In case of multiple resolution cases, the face is aligned and smoothened by applying a Gaussian blur, and the face image is then mapped with Affine Wrap to simulate the artifacts. The CNN model was trained to detect the existence of artifacts in the face region and surroundings. The presented model was compared with the four states of the models, VGG16, ResNet50, ResNet101, and ResNet152. The model tested over UADFV and Deepfake TIMIT databases shows promising results regarding these databases' state-of-the-art features. A study in [2] surveyed the face manipulation techniques and artifacts. They proposed a methodology to identify artifacts like eye color, reflection, and missing details in teeth formation and eye area. In this regard, they have proposed a novel approach using Bi-granularity artifacts (BiG-Arts).

Yang et al. [12] presented a scheme to detect Deepfakes through head movement. The Deepfake images are created by interlacing fake face images with the actual image, and while doing so, the process leaves artifacts in the 3D head position. Analyzing 3D head estimation and inconsistency, classification can be performed to detect the modification. They proposed an SVM classifier, and the results were evaluated for each UADFV dataset. The offered method was evaluated using the frames of UADFV. Hsu et al. [13] presented a common fake feature network (CFFN) model alongside pairwise learning to detect Deepfake. A two-phase procedure was followed for feature extraction. CFFN used Siamese architecture, and classification was performed through CNN.

Another study in [14] presented an optical flow scheme based on a convolutional neural network (CNN). The proposed approaches detect the Deepfake on a single video frame, where the optical flow approach catches the inter-frame dissimilarities. An experiment is performed on VGG16 and ResNet50, and results are tested over the Face-Forensic++ dataset, showing promising performance. Likewise, a study in [15] detects artifacts' presence among real and Deepfake by examining the GAN pipeline. The proposed detection scheme chooses color feature as a detection parameter and a pre-trained machine learning SVM classifier. The method achieved 70% accuracy when evaluated over a dataset named NIST MFC2018.

The classical deepfake detection methods use a convolutional neural network (CNN) to detect real or fake images based on a dataset of still images. They are unable to perform the detection of videos. Results show that sequential features can be quite crucial for detecting deepfake videos, as some of these features can be detected in videos only, e.g., it has been observed that in deepfake videos, the eye blink rate is much lower than in real videos [14]. Fig. 1 shows the taxonomy of various methods, techniques, and classifications applied to deepfake detection methods.

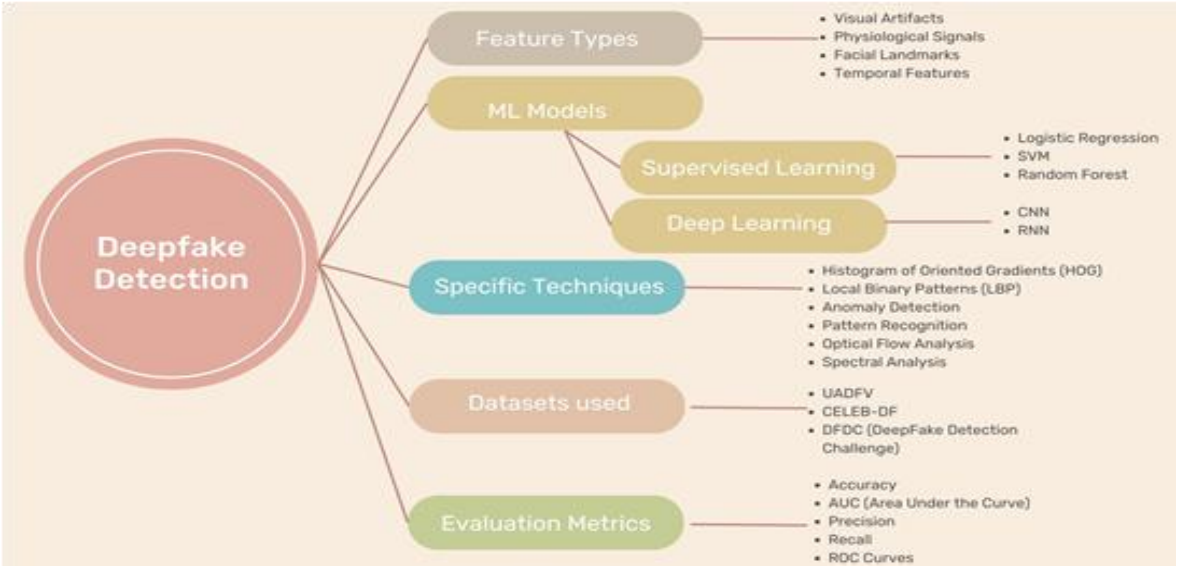


Fig. 1. Classification of deepfake detection methods.

Whereas Table II classifies and summarizes state-of-the-art methods and approaches in a hierarchical manner. Starting with main categories, that includes the feature set, followed by machine learning models and techniques, dataset used, and evaluation metrics applied. In the second column it segregates the subtypes of each category and consequently the description of each category.

TABLE II. SUMMARY OF TECHNIQUES APPLIED TO DEEPFAKE DETECTION

| Main Category | Subcategory | Description |
|---|---|---|
| Feature Types | Visual Artifacts [1], [4], [16] | Color Inconsistencies: Abnormal color dissimilarities or mismatches in different areas of the face. |
| | | Blurring and Boundaries: Blurred edges around the face or other areas of the image where the forged overlay blends with the real background. |
| | | Texture and Lighting: Variations in texture and lighting that do not match the neighbouring context. |
| | Physiological Signals [10], [12], [17], [18] | Eye Blinking: Abnormal blinking patterns that are either too frequent or too infrequent as compared to natural human behaviour. |
| | | Lip Sync: Reduced synchronization between lip movements and the audio, demonstrating that the speech may be dubbed or artificially generated. |
| | | Head Movements: Unnatural head movements that do not align with the rest of the body or the environment. |
| | Facial Landmarks [19]–[21] | Facial Expression Analysis: Analyzing irregularities in facial expressions, which might not align logically. |
| | | Landmark Deformation: Distortions in the placement of facial landmarks such as eyes, nose, and mouth during various expressions or movements. |
| | Temporal Features [21], [22] | Frame-to-Frame Consistency: Checking for irregularities across successive frames of a video that may show fiddling. |
| | | Optical Flow: Analyzing the motion patterns in video sequences to identify irregularities. |
| Machine Learning Models | Supervised Learning [16], [22] | Logistic Regression: A simple, binary classification algorithm used for initial investigation. |
| | | Support Vector Machines (SVM): Effective for high-dimensional data. |
| | | Random Forests: An ensemble learning method that combines several decision trees for enhanced accuracy. |
| | Deep Learning [16], [20] | Convolutional Neural Networks (CNNs): Excellent for extracting spatial features from images and videos. |
| | | Recurrent Neural Networks (RNNs): Appropriate for capturing sequential dependencies in video sequences. |
| | | Capsule Networks: Capture spatial hierarchies and relationships. |
| | | Attention Mechanisms: Focus on the most pertinent parts of the input data. |
| | Hybrid Models[23] | CNN + RNN: Combining spatial and temporal features for a detailed analysis. |
| | | Ensemble Methods: Using multiple models to augment detection performance by using their combined strengths. |
| Specific Techniques | Handcrafted Feature Extraction [24] | Histogram of Oriented Gradients (HOG): Detecting particular facial features by examining gradients and orientations in the image. |
| | | Local Binary Patterns (LBP): Analyzing texture by associating each pixel with its neighbors. |
| | Deep Learning-Based Extraction [25] | Pre-trained Networks: Utilizing networks like VGG16, ResNet, which have been pre-trained on large datasets, for feature extraction. |
| | | GAN Discriminators: Using the discriminator component of GANs to identify fake content. |
| | Statistical Analysis [26] | Anomaly Detection: Identifying outliers in facial features and movements that do not follow the likely patterns. |
| | | Pattern Recognition: Identifying and analyzing particular patterns in physiological signals and visual artifacts. |
| | Signal Processing [26] | Optical Flow Analysis: Identifying motion discrepancies within the video. |
| | | Spectral Analysis: Analyzing frequency components of facial movements to distinguish anomalies. |
| Datasets Used | Publicly Available Datasets [27] | UADFV: Contains real and fake videos specifically created for deepfake detection research. |
| | | Celeb-DF: A large-scale dataset with high-quality deepfake videos. |
| | | DFDC (DeepFake Detection Challenge): A diverse dataset from the DeepFake Detection Challenge, containing numerous deepfake videos for benchmarking. |
| Evaluation Metrics | Accuracy [28], [29] | The overall percentage of appropriately classified instances (both real and fake). |
| | AUC (Area Under the Curve) [28] | Measures the capability of the model to differentiate between classes, providing insight into its performance across different thresholds. |
| | Precision and Recall [30] | Precision: The ratio of true positives to predicted positives, demonstrating the accuracy of the positive predictions. |
| | | Recall: The ratio of true positives to actual positives, demonstrating the capability to identify all positive instances. |
| | F1-Score [29] | The harmonic mean of precision and recall, providing a stable measure of the model's performance. |
| | Receiver operating characteristic (ROC) Curves [31] | Receiver Operating Characteristic curves, which visualize the trade-off between true positive rate and false positive rate across different thresholds. |

### A. Contribution

The contribution of this research paper is as follows:

- This research work extracts facial feature eye blink using a real-time blinking method called Eye Aspect Ratio (EAR). To detect the second facial feature, the nose's position, we utilize a pre-trained machine learning Haar cascade classifier with 97% accuracy for efficient detection.
- To counter this recent threat, this research work used a supervised learning method to identify the deepfake videos from the real ones. The results show that the proposed methodology is quite efficient in distinguishing the real videos from the deepfake videos.
- The presented model is evaluated using pre-trained Eye Aspect Ratio (EAR). The proposed scheme detected a blinking ratio of 34.1/ min in real video and 3.4/ min in fake video.

This research paper is organized as follows: Related work is given in Section II. Section III discusses the proposed methodology, Section IV presents the results and discussion, and Section V discusses the conclusion.

## III. Methodology

This section proposes a method to detect Deepfake videos by extracting facial features. Fig. 2 depicts the proposed methodology. Deepfake video detection differs from image detection, as manipulation is carried out frame by frame and contains temporal characteristics. We are using two features to extract the modification:

- Eyeblink.
- Nose position.

Generally, it is observed that individual Deepfake videos show abnormal eye blinking, which is less frequent compared to normal human blinking behavior. An adult human can blink in 2 to 10 seconds, and each blink consumes 0.1 and 0.4 seconds. Every individual has different blink patterns concerning the open and closed state of the eye. Typically, Deepfake methods are trained on images that possess an open eye state, so it is difficult for Deepfake methods to generate synthesized videos with normal blinking behavior. Eyeblink contains temporal dependency and is expected to appear as temporal artifacts across the frame as manipulation is performed over frame-by-frame sequence. A face landmark detector is used in the proposed study to detect the face and the eye's open /closed state using the DLIB model. Face landmarks locate the whole set of feature points of the face, like lips, eyes, nose, and contour, which can be detected from the face area. The eye blink's first feature is calculated by computing the Eye Aspect Ratio (EAR) in each video frame. EAR of the person depends on the eye's landmark locations, and it is a constant value when the person's eye state is opened and falls to 0 when the eye is closed [13].

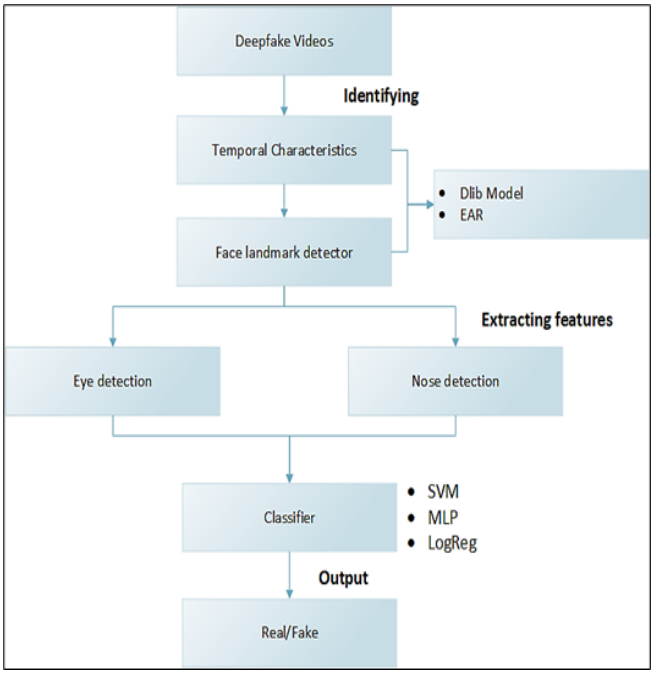


Fig. 2. Proposed methodology.

The following formula calculates EAR:

$$EAR_i = \frac{||\mathcal{P}_2-\mathcal{P}_6||+||\mathcal{P}_3-\mathcal{P}_5||}{2||\mathcal{P}_1-\mathcal{P}_4||} \quad (1)$$

Where $P_i$ (i=1, 2…, 6) are the eye's landmark points, we do not know the deep learning algorithms for eye blink detection. Fig. 3 and Fig. 4 demonstrate the eye blink and nose positions identified in real and fake videos. Overview of the workflow for detecting eye blinks in real and fake videos. The Haar cascade classifier is used for the second feature, i.e., nose; the machine learning approach has rapid detection capability with approximately 95% accuracy. We are using a multiscale Haar cascade Classifier to detect face and nose position in the video stream. We are using the first data set to extract Features, such as UADFV, which contains both real and fake videos. For example, UADFV features the eye blink and nose position extracted from the data set with 98 videos. The dataset collected 49 real and 49 fake videos with 32,752 frames. These videos are generated from the DNN model with FakeApp and are 2 to 44 seconds long, with an average of 11.26 seconds.

Tables III and Table IV describe the UADFV and Celeb-DF datasets, respectively. Moreover, they show the number of videos in each dataset with real and fake counterparts, their average length, and frame rate (frames per second).

TABLE III. Dataset 1 UADFV Specification

| Dataset | Number of videos | Average length | Frames per second |
|---|---|---|---|
| REAL | 49 | 11.26 | 28FPS |
| FAKE | 49 | 11.26 | 28FPS |

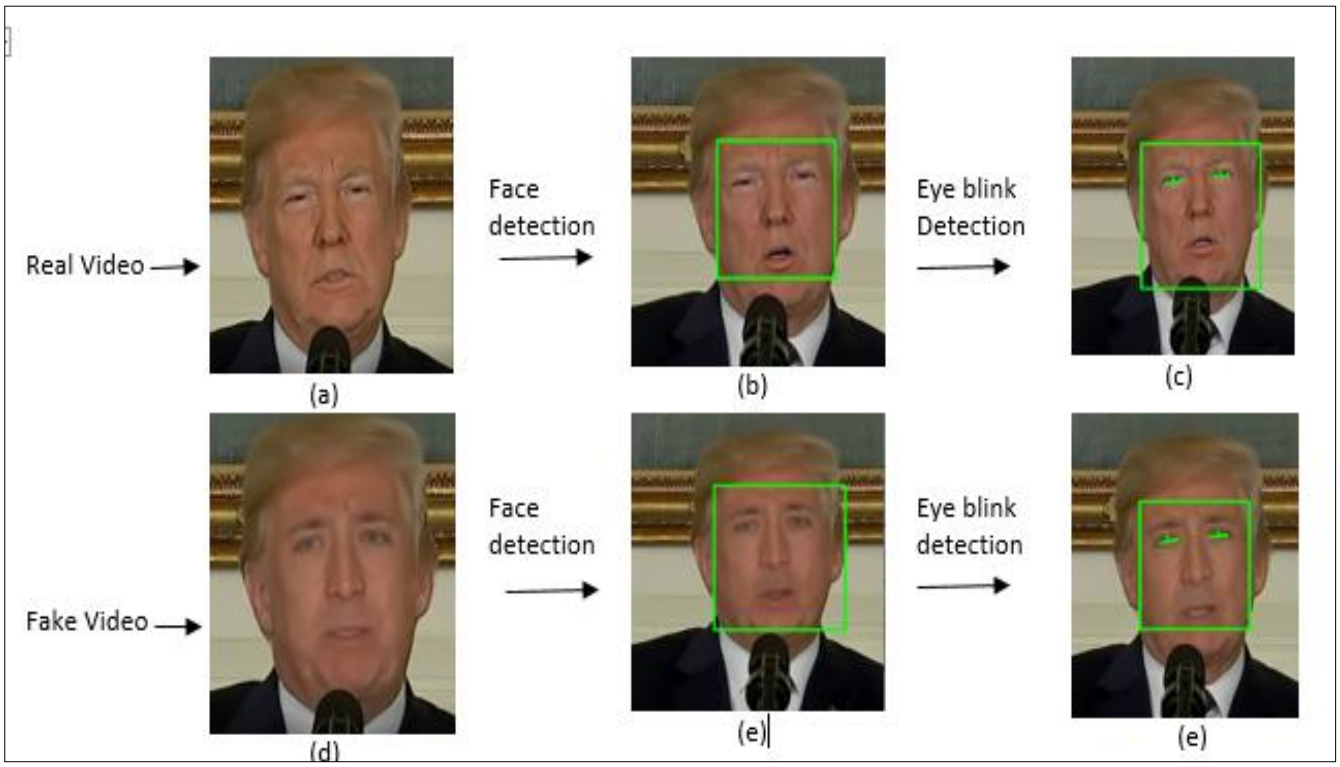


Fig. 3. Overview of workflow detecting eye blink in real and fake videos.

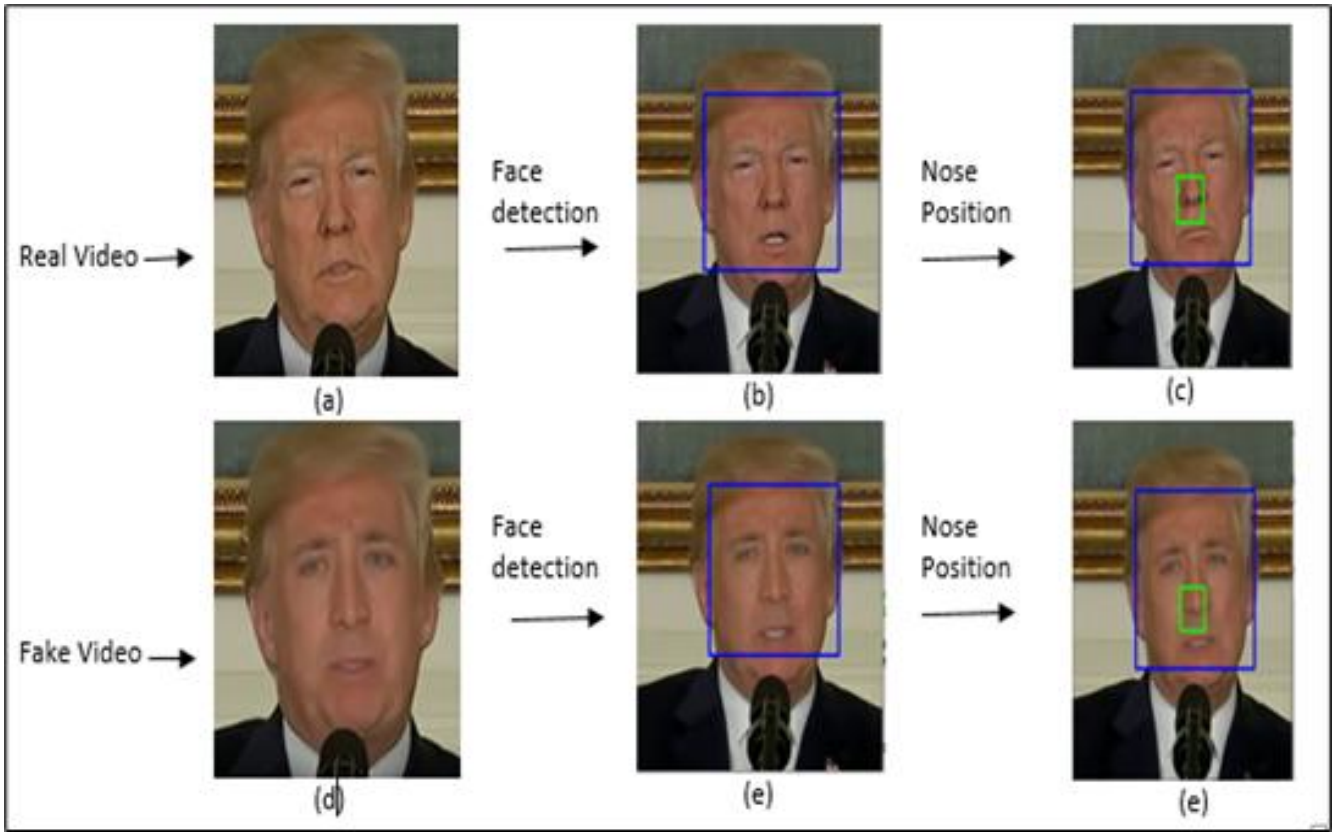


Fig. 4. Overview of workflow detecting nose positions in real and fake videos.

Celeb-DF is a new dataset proposed by Li et al. [14] using refined generating algorithms with improved quality videos and less visible artifacts. The data set used for this experiment is Celeb-DF.

TABLE IV. DATASET 2 CELEBDF SPECIFICATION

| Dataset | Number of videos | Average length | Frame per second |
|---|---|---|---|
| REAL | 408 | 13 sec | 30FPS |
| FAKE | 795 | 13 sec | 30FPS |

For a more in-depth analysis, 50 YouTube-real videos and 50 Celeb-synthesis videos datasets are also considered in addition to the two datasets mentioned above for the performance analysis of classifiers.

## IV. RESULTS AND DISCUSSIONS

The extracted facial features are trained and evaluated on the datasets for three different classifiers. In the next step, a classifier was trained to distinguish between real and fake videos. Fig. 5 shows the receiver operating characteristic (ROC) curve of the proposed classifiers for the proposed feature and classifiers.

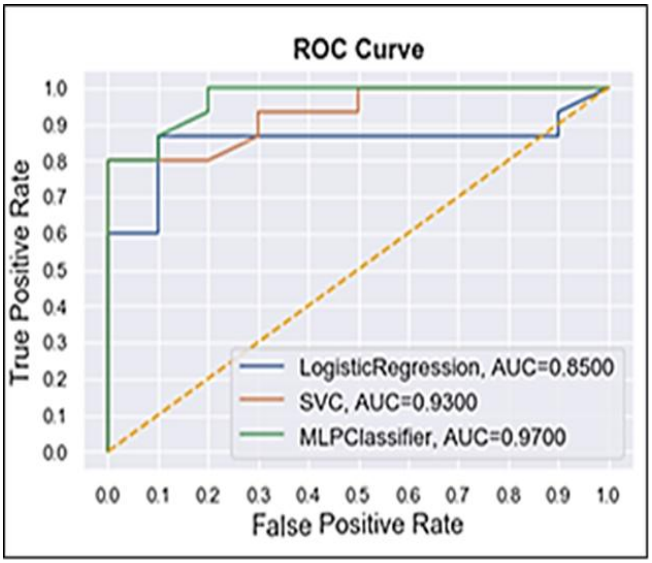


Fig. 5. ROC Comparison for UADFV dataset.

Fig. 6 shows the classification ROC curve analysis on the proposed datasets on extracted facial features for different classifiers. We refer to the supervised machine learning classifiers, SVM, Logistic Regression, and MLP.

The results show in Table V that the classifiers can adequately distinguish between the real and fake sets of videos. The Celeb-DF dataset's performance is low compared to the UADFV because it contains fewer visible artifacts that are difficult to identify. The proposed performance-based method is compared with other methods on the same datasets: UADFV and Celeb-DF.

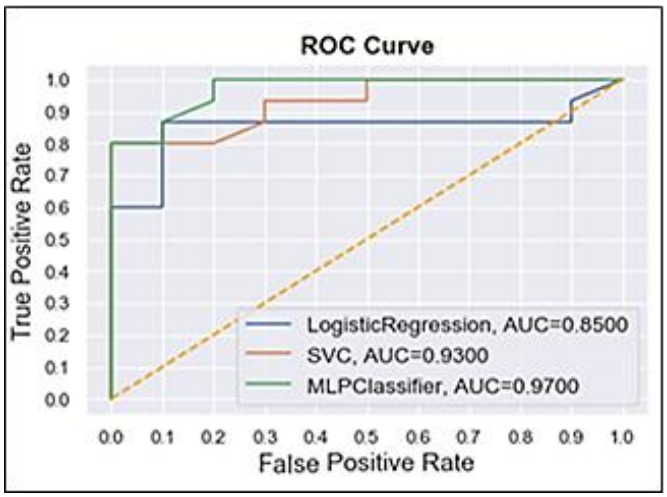


Fig. 6. ROC comparison for CELEBDF dataset.

TABLE V. PERFORMANCE COMPARISON OF MODELS FOR TWO DATASETS

| Methods/Classifiers | UADFV | Celeb-DF |
|---|---|---|
| HeadPose-SVM [1] | 89.0 | 54.8 |
| VA-LogReg | 70.2 | 48.8 |
| VA-MLP [2] | 54.0 | 46.9 |
| FWA-CNN [3] | 97.4 | 53.8 |
| iCaps-Dfake [14] | - | 86% |
| RNN [31] | - | 73.41% |
| Capsule network [5] | - | 57.5% |
| CNN[19] | 84.3 | 54.8 |
| SVM | 93.0 | 64.0 |
| MLP | 97.0 | 75.0 |
| LogReg | 85.0 | 72.0 |

Detection is performed on the feature "Head Pose" [12] using an SVM classifier. The classifiers generated AUC (%) performance of 89.0 on UADFV and 54.8% on the CelebDF dataset. Visual artifacts like eyes, teeth, and facial texture are identified by applying Logistic Regression and MLP. The methods' AUC performances are 70.2% and 48.8% on the datasets, respectively [3]. Face Warping artifacts [11] are classified by using a CNN. The classifiers show the AUC performance of 97.4% for the UADFV dataset and 53.8% for the Celeb-DF dataset. For iCaps-Dfake method [14], performance on Celeb-DF dataset is 86%. For the RNN [31] based classifier, the performance of the Celeb-DF dataset was 73.41%. For the capsule network [5], the performance of the Celeb-DF dataset is 57.5%. For CNN [19], performance on the UADFV dataset is 84.3%, and performance on the Celeb-DF is 54.8%. This research used SVM, MLP, and Logistic Regression, which shows strong performance for deepfake detection on UADFV and Celeb-DF datasets. MLP exhibited the best accuracy among the three methods, i.e., 97% on UADFV and 75% on Celeb-DF. SVM achieved 93% on UADFV and 64% on Celeb-DF. For LogReg, 85% accuracy is achieved on the UADFV dataset and 72% on Celeb-DF.

## V. Conclusion

The proposed method detects fake blinks in the UADFV dataset at a rate of 0.6 per 60 seconds and real blinks at 7.4 per 60 seconds. Similarly, in the Celeb-DF dataset, we observe a rate of 9.8 real blinks and 5.04 fake blinks per minute. Given that the average human blink rate is around 10 blinks per minute, the generated videos fall below this standard. Additionally, we note that the nose position in fake videos from the UADFV dataset deviates from its original position more than in the Celeb-DF dataset. Both features achieve a higher performance with an Area Under the Curve (AUC) of 97% on UADFV and 75% on Celeb-DF. For future work, there are several directions we plan to explore to enhance our current findings. We aim to investigate new deep learning architectures for more effective results. Furthermore, we will continue searching for facial artifacts and other physiological signals often overlooked in synthesized videos.

## Authors' Contributions

Conceptualization, Jamaluddin Mir and Atta Rahman; Data curation, Dhiaa Musleh; Formal analysis, Gohar Zaman, Asiya Abdus Salam and Jamal Alhiyafi; Funding acquisition, Mustafa Jamal Gul, Jamal Alhiyafi and Aghiad Bakry; Investigation, Farhan Ali Dhiaa Musleh, Jamal Alhiyafi and Mohammed Gollapalli; Methodology, Ayesha Aslam, Jamaluddin Mir, Gohar Zaman and Atta Rahman; Resources, Mohammed Gollapalli; Software, Ayesha Aslam and Aghiad Bakry; Supervision, Jamaluddin Mir; Validation, Asiya Abdus Salam, Dhiaa Musleh and Aghiad Bakry; Visualization, Mohammed Gollapalli; Writing – original draft, Ayesha Aslam; Writing – review & editing, Gohar Zaman, Mustafa Jamal Gul, Atta Rahman, and Farhan Ali. Farhan Ali and Atta-Rahman have equal contributions.

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Conflicts of Interest: The authors declare no conflicts of interest.

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# Hybrid Approach for Early Road Defect Detection: Integrating Edge Detection with Attention-Enhanced MobileNetV3 for Superior Classification

Ayoub Oulahyane[1]*, Mohcine Kodad[2], El Houcine Addou[3], Sofia Ourarhi[4], Hajar Chafik[5]
MATSI Laboratory, ESTO, Mohammed First University, Oujda, 60000, Morocco[1, 2]
LANO Laboratory, FSO-ESTO, Mohammed First University, Oujda, 60000, Morocco[3]
2GPMH Research Lab, FSO, Mohammed First University, Oujda, 60000, Morocco[4]
LCELHN Laboratory, FLSHO, Mohammed First University, Oujda, 60000, Morocco[5]

***Abstract*—The early detection of road defects is critical for maintaining infrastructure quality and ensuring public safety. This research presents a hybrid approach that combines edge detection techniques with an enhanced deep learning model for efficient and accurate road defect classification. The process begins with edge detection to highlight structural irregularities, such as cracks and potholes, by emphasizing critical features in road surface images. These pre-processed images are then fed into a classification model based on MobileNetV3, augmented with an attention mechanism to improve feature weighting and model focus on defect-prone regions. The proposed system was evaluated on a Crack500 dataset of road surface images, achieving a classification accuracy of 96.2%. This demonstrates significant improvement compared to baseline models without edge detection or attention enhancements. The edge detection stage efficiently reduces noise, while the attention-augmented MobileNetV3 ensures robust feature discrimination, making the approach suitable for real-time and resource-constrained deployment scenarios. This study highlights the effectiveness of combining classical image processing with advanced neural network techniques. The proposed system has the potential to optimize road maintenance workflows, operational costs, and improve road safety by enabling early and precise defect identification.**

***Keywords*—Road defect detection; edge detection; attention mechanism; MobileNetV3***

## I. Introduction

Road infrastructure plays a fundamental role in economic development, public safety, and the overall quality of life [1], [2]. Properly maintained roads ensure the smooth flow of goods, services, and people, contributing to societal efficiency and growth. However, road defects such as cracks, potholes, and surface deformities are inevitable due to wear and tear, extreme weather conditions, and high traffic loads [3], [4]. These defects, if not detected and addressed promptly, can escalate, leading to costly repairs, increased accident risks, and disruptions to transportation systems. Consequently, early and accurate detection of road defects is critical to minimize maintenance costs and enhance road safety [5].

Traditionally, road inspections have relied on manual methods or simple imaging systems, which often fall short in terms of accuracy, scalability, and efficiency [6]. Manual inspections are labor-intensive, subjective, and unsuitable for large-scale applications, while basic imaging systems struggle with environmental challenges such as poor lighting, shadow interference, and complex road textures [7]. This has necessitated the development of automated approaches that are not only accurate but also adaptable to real-world conditions [8].

Despite significant progress in computer vision and deep learning, current automated systems still struggle to accurately detect small or subtle defects in complex and dynamic environments. There remains a clear need to develop lightweight and effective models that can maintain high detection accuracy without imposing high computational demands, ensuring their applicability in real-world settings. This study addresses the challenge by investigating how preprocessing techniques, particularly edge detection, can be combined with deep learning models to enhance road defect detection performance. It also explores whether incorporating an attention mechanism into a lightweight model such as MobileNetV3 can improve sensitivity to defect-specific features and overall classification accuracy. Furthermore, the research examines the impact of integrating traditional image processing with deep learning to develop a more robust and reliable detection framework.

The objectives of this work are to design and implement a hybrid methodology that combines edge detection with an attention-augmented MobileNetV3 model, to preprocess road surface images by emphasizing defect-relevant features while minimizing background noise, and to evaluate the proposed framework's performance against existing methods using benchmark datasets.

In this study, Fig. 1 provides a visual representation of various types of road surface cracks, which are critical indicators of pavement deterioration. These include common defects such as longitudinal, transverse, and block cracks, among others. The figure serves to underscore the diverse and complex nature of road defects, which necessitate precise and efficient detection methodologies.

By examining these crack types, the paper establishes the motivation for adopting a hybrid approach that combines edge detection techniques with an attention-augmented MobileNetV3 model [9]. This innovative framework aims to enhance the accuracy and robustness of road defect classification, ensuring timely maintenance and improved infrastructure resilience.

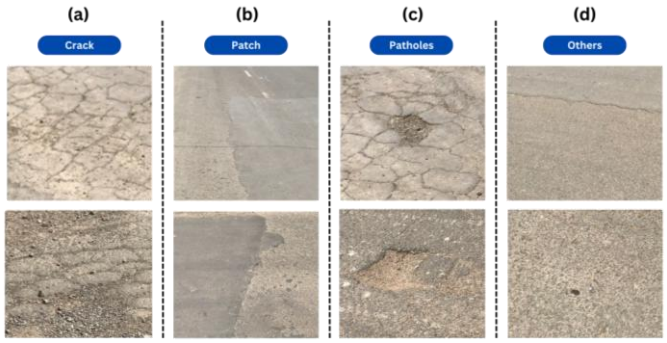


Fig. 1. Illustration of various types of road surface cracks, highlighting the importance of early detection for maintenance and safety.

This paper proposes a hybrid methodology for road defect detection that leverages the strengths of edge detection and a deep learning model enhanced with an attention mechanism. The process begins with edge detection to preprocess road surface images, emphasizing defect-relevant features while reducing background noise and redundant information. These refined images are then input into a MobileNetV3-based neural network, which is augmented with an attention mechanism to improve its focus on critical features. The attention mechanism dynamically prioritizes defect-specific regions in the feature maps, enhancing the model's ability to detect subtle defects such as hairline cracks or small potholes.

The remainder of this paper is organised as follows. Section II provides a detailed overview of related work in road defect detection and highlights the gaps that this study aims to address. Section III describes the proposed methodology, including the integration of edge detection and the MobileNetV3 architecture with attention mechanisms. Section IV discusses the experimental setup, dataset, and performance metrics. It also presents and analyzes the results, while Section V concludes the paper with insights, limitations, and potential directions for future research.

This work aims to contribute to the growing field of automated infrastructure monitoring by providing a practical, scalable, and efficient solution for early road defect detection, which can significantly impact road maintenance strategies and public safety worldwide.

## II. Related Work

Road defect detecting has garnered considerable attention in recent years due to its significance in maintaining infrastructure safety and functionality. A variety of approaches, ranging from traditional image processing methods to cutting-edge deep learning techniques, have been proposed to address the challenges posed by road defect identification in real-world scenarios.

### A. Maintaining the Integrity of Specifications

Traditional computer vision techniques, such as edge detection algorithms, have been widely used for identifying structural discontinuities in road surfaces [10]. Methods like Sobel [11], Canny [12], and Laplacian filters [13] efficiently highlight features such as cracks and potholes by emphasizing abrupt changes in pixel intensity. While computationally efficient, these techniques often lack robustness in noisy environments or under varying lighting conditions. Nonetheless, edge detection remains a valuable preprocessing tool, as it helps reduce noise and isolate defect-prone regions, providing a foundation for more advanced classification models.

### B. Deep Learning in Road Defect Detection

With the advent of deep learning, researchers have shifted focus toward convolutional neural networks (CNNs) for automated defect detection. For instance, the YOLO family of object detection models has shown remarkable capabilities in real-time applications. The RDD-YOLOv5 model integrates a self-attention mechanism to enhance the precision of crack detection, achieving a high mAP of 91.48% [14]. Similarly, BL-YOLOv8, which incorporates BiFPN and LSK-attention, optimizes both accuracy and computational efficiency. By reducing model size and parameter volume, it becomes suitable for deployment in resource-constrained settings [15].

### C. Attention Mechanisms

Attention mechanisms have emerged as a powerful enhancement in deep learning models, enabling them to focus on the most relevant regions of an image. Studies combining attention mechanisms with ensemble learning methods have demonstrated significant improvements in road defect detection. For example, a multi-depth attention mechanism has been successfully employed to prioritize defect-specific features, achieving superior performance across diverse datasets [16].

These mechanisms are particularly effective when integrated into light-weight architectures, such as MobileNet, to improve performance without compromising efficiency.

### D. Transfer Learning and Lightweight Models

Transfer learning has proven to be indispensable for road defect detection, especially in scenarios with limited annotated data. By fine-tuning pre-trained models like MobileNet, researchers can leverage knowledge learned from large-scale datasets to improve defect detection accuracy [17]. MobileNetV3, in particular, has gained attention for its lightweight architecture, making it ideal for real-time applications on mobile and edge devices[18]. Incorporating attention mechanisms into MobileNetV3 further enhances its ability to classify defects, even in challenging conditions with shadows or occlusions.

### E. Hybrid Approaches

Hybrid methodologies that combine traditional image processing with deep learning represent a promising direction in road defect detection. For instance, edge detection can preprocess images to isolate potential defect regions, reducing noise and computational complexity before feeding the images into a CNN [19]. When coupled with attention-augmented architectures, these hybrid approaches strike a balance between efficiency and accuracy. This synergy allows the system to handle subtle defects, such as fine cracks, and more pronounced issues, like large potholes [20].

### F. Recent Surveys and Challenges

Comprehensive surveys have highlighted the current trends and challenges in road defect detection using deep learning. Key issues include the scarcity of large, labeled datasets, variations in environmental conditions, and the trade-off between accuracy

and computational efficiency [21]. To address these, researchers are exploring novel architectures, multi-task learning, and adaptive methods that enhance generalization across diverse road conditions.

## III. METHODOLOGY

This section outlines the research methodology used in this study, focusing on data collection and preprocessing, the hybrid approach involving edge detection and an attention-augmented MobileNetV3 model, training procedures, and evaluation metrics.

### A. Data Description

A diverse dataset of road surface images was compiled to include various defect types, such as cracks, potholes, and surface irregularities, captured under different environmental conditions, including variations in lighting, weather, and road textures. The images were sourced from high-resolution open-access datasets like CRACK500 [22], supplemented with publicly available road damage datasets to enhance the collection. Efforts were made to ensure diversity by accounting for geographical and environmental variations, enabling the model to generalize effectively across different regions and conditions. The dataset was split into training (70%), validation (15%), and testing (15%) subsets to facilitate robust model training and evaluation.

### B. Preprocessing with Edge Detection

Edge detection was applied to preprocess the road surface images, emphasizing defect-related features while reducing irrelevant noise. Popular edge detection algorithms, such as the Canny and Sobel methods, were employed to identify structural discontinuities. Among these, the Canny edge detection algorithm was chosen for its robustness in detecting edges across a wide range of conditions [23], particularly its ability to efficiently handle noise and preserve fine structural details (see Fig. 2).

The Canny algorithm involves several steps, including:

- Gaussian Smoothing: To reduce noise, the image is convolved with a Gaussian filter:

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{\frac{x^2+y^2}{2\sigma^2}}$$

where σ is the standard deviation of the Gaussian kernel.

- Gradient Magnitude and Direction: The intensity gradients are computed using partial derivatives in the x and y directions (often approximated using Sobel filters):

$$M(x,y)=\sqrt{(G_x^2+G_y^2)}$$

$$\theta(x,y)=\arctan(G_x/G_y)$$

Where $G_x$ and $G_y$ are the gradients in the x and y directions, respectively.

- Non-Maximum Suppression: Thin out edges by suppressing non-maximum gradient values in the direction of the gradient.
- Double Thresholding and Edge Tracking: Apply two threshold values (σ ,T low and T high) to classify pixels as strong edges, weak edges, or non-edges. Weak edges connected to strong edges are retained.

The edge-detected images served as additional input channels or as standalone images for training the deep learning model, depending on the experimental configuration.

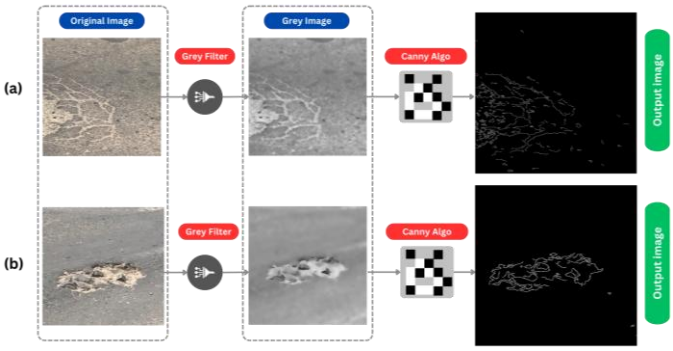


Fig. 2. Image processing workflow: original to grayscale via filter, then edge detectation with the canny algorithm.

### C. Model Architecture

The hybrid approach integrated edge detection with a deep learning architecture based on MobileNetV3 enhanced with an attention mechanism, as shown in Fig. 3.

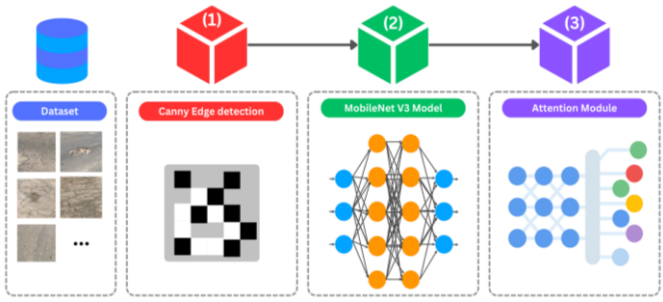


Fig. 3. Summary of the proposed architecture.

MobileNetV3: Selected for its lightweight architecture and efficiency, MobileNetV3 serves as the backbone for defect classification.

Attention Mechanism: An attention module, such as SE-blocks (Squeeze-and-Excitation) or CBAM (Convolutional Block Attention Module), was integrated into the network to dynamically weight critical features, enhancing the model's focus on defect-prone regions.

Input Pipeline: The preprocessed (edge-detected) images were input into the MobileNetV3 model, with the attention mechanism applied at intermediate layers to improve feature representation shown in Fig. 4.

The provided architecture integrates lightweight and efficient design with advanced attention mechanisms to enhance feature learning for crack detection. It employs SE (Squeeze-and-Excitation) blocks [24] to improve channel-level attention by learning channel weights and CBAM (Convolutional Block Attention Module) [25], to refine spatial feature distribution.

The depthwise separable convolutions maintain computational efficiency while expanding the capacity for complex feature learning. Application-specific modifications ensure the receptive field captures both large and small cracks, with attention mechanisms suppressing irrelevant noise and amplifying crack-specific features. This robust pipeline achieves effective classification across four output classes.

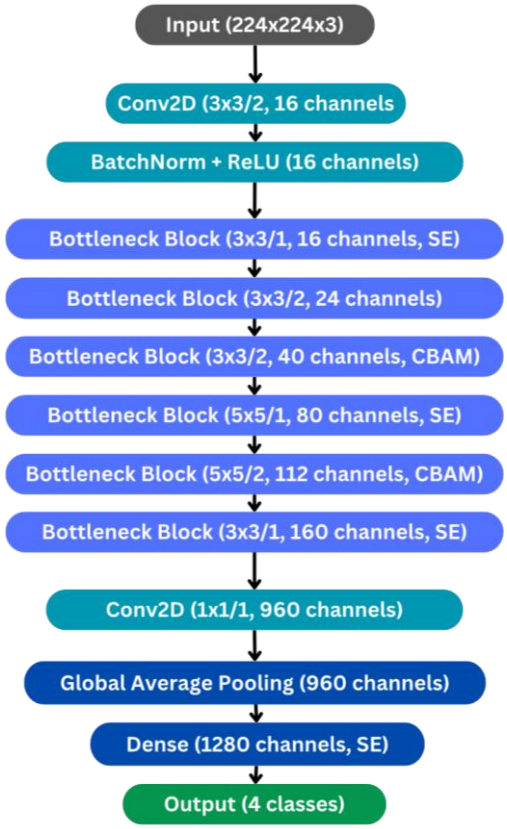


Fig. 4. The main layer architecture proposed for the hybrid MobileNet V3.

### D. Evaluation Metrics

To evaluate the performance of the proposed approach, several metrics were employed, accompanied by their respective mathematical formulations. Accuracy (A) was used to measure the overall correctness of defect classification and is calculated as:

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. Precision (P) and Recall (R) were utilized to assess the model's ability to accurately identify specific defect types. Their formulas are given by:

$$P = \frac{TP}{TP + FP}, \qquad R = \frac{TP}{TP + FN}$$

The F1-Score (F1) was calculated to provide a harmonic mean of precision and recall, expressed as:

$$F1 = 2 . \frac{P . R}{P + R}$$

Finally, Inference Time (Ti) was measured to evaluate the computational efficiency and suitability for real-time applications, defined as the average time taken by the model to process a single input. These metrics collectively offer a comprehensive evaluation of the model's performance.

### E. Comparative Analysis

The proposed hybrid model was benchmarked against a diverse set of approaches to comprehensively evaluate its effectiveness in defect detection. Among the baseline models, standalone MobileNetV3 and traditional edge detection-based techniques were used to establish a fundamental performance comparison. Additionally, the model was evaluated against state-of-the-art approaches, including advanced YOLO-based architectures and other attention-enhanced frameworks that are widely recognized for their robust performance in object detection tasks. The comparative analysis revealed that the integration of edge detection and attention mechanisms provided significant advantages, especially in scenarios where defects were subtle or obscured by complex environmental conditions, such as varying lighting, background clutter, or noise. This underscores the hybrid model's ability to deliver precise and reliable defect detection under challenging real-world conditions.

### F. Experimental Setup

*1) Hardware:* The training and evaluation processes were conducted on a high-performance GPU-accelerated system equipped with an NVIDIA RTX 3080 GPU, ensuring efficient handling of computationally intensive tasks. For additional benchmarking, experiments were also validated on an NVIDIA Tesla V100 to assess scalability and performance consistency across different hardware.

*2) Frameworks:* The hybrid model was implemented and trained using TensorFlow and PyTorch frameworks, chosen for their versatility and compatibility with GPU acceleration. TensorFlow facilitated efficient deployment pipelines, while PyTorch offered dynamic computation graph capabilities, enhancing model prototyping and debugging.

*3) Software tools:* Data preprocessing was carried out using OpenCV for image manipulation tasks, such as resizing, filtering, and edge detection, and NumPy for efficient numerical operations. Visualization of training metrics and results was accomplished with Matplotlib and Seaborn libraries, ensuring clear and interpretable performance analysis.

*4) Dataset configuration:* The dataset was split into training, validation, and test sets in a ratio of 70:20:10. Data augmentation techniques, including random rotation, flipping, and noise injection, were applied to enhance model robustness and mitigate overfitting.

*5) Hyperparameters:* Key hyperparameters were carefully tuned to optimize model performance. The learning rate was set at 0.001 with a decay schedule to ensure gradual convergence. A batch size of 32 was used, balancing memory constraints and training efficiency. The Adam optimizer was employed for gradient updates due to its adaptability and convergence properties.

## IV. Results and Discussion

In Fig. 5. The graphs demonstrate the strong performance of the hybrid model, with both training and validation accuracy rapidly improving to ~96% and stabilizing, while training and validation loss decrease significantly and plateau at low values (~0.2-0.3) by the end of 70 epochs. The minimal gap between training and validation metrics indicates excellent generalization and low overfitting, validating the model's robustness. These trends align with the quantitative results, showcasing high accuracy (96.2%), precision, and recall, as well as efficient inference time (18ms). The integration of edge detection and attention mechanisms clearly enhances feature extraction and model stability, making it well-suited for real-time crack detection tasks.

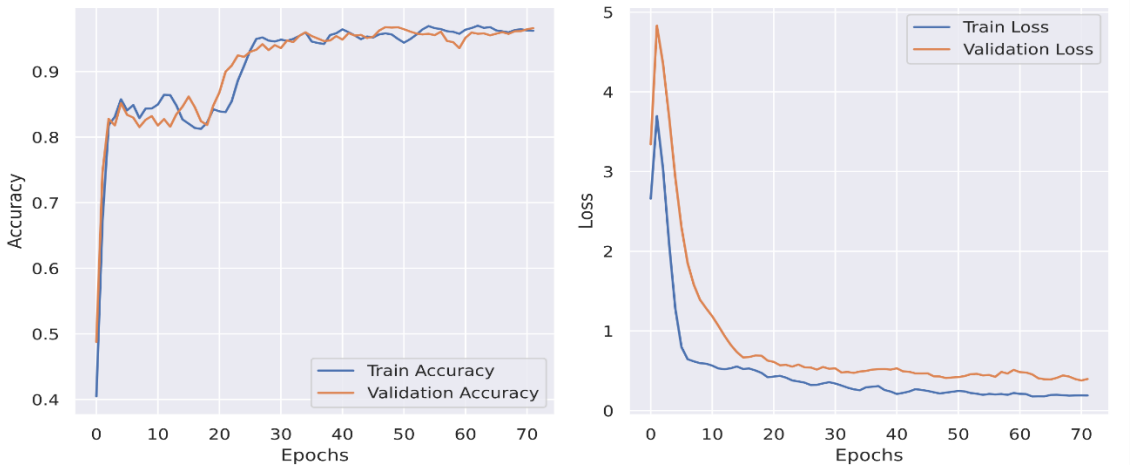


Fig. 5. Training and validation accuracy and loss curve showing 90% accuracy, rapid convergence, trained over 70 epochs.

The results in Table I, clearly highlight the superiority of the proposed hybrid model, which combines edge detection with MobileNetV3 enhanced by an attention mechanism. Achieving an outstanding accuracy of 96.2%, the hybrid model significantly outperforms the standalone MobileNetV3 (90.5%) and YOLOv5-based model (91.48%), demonstrating its ability to classify road defects with a high degree of reliability across various environmental and road conditions. This improved accuracy indicates the hybrid approach's ability to better capture subtle and complex defect features, such as fine cracks and irregular textures, which are often missed by simpler models.

TABLE I. Comparison of Hybrid Model, MobileNetV3, and YOLOv5 on Accuracy, Precision, Recall, F1-Score, and Inference Time

| Metric | Proposed Model (Hybrid) | Standalone MobileNetV3 | YOLOv5-Based Model |
|---|---|---|---|
| Accuracy (%) | **96.2** | 90.5 | 91.48 |
| Precision (%) | **94.8** | 88.9 | 92.1 |
| Recall (%) | **95.6** | 89.2 | 91.3 |
| F1-Score (%) | **95.2** | 89.0 | 91.7 |
| Inference Time (ms) | **18** | 15 | 22 |

In addition to accuracy, the hybrid model excels in other key metrics. Its precision of 94.8% outshines both the MobileNetV3 (88.9%) and YOLOv5-based (92.1%) models, indicating its ability to correctly identify road defects while minimizing false positives. Similarly, the hybrid model's recall of 95.6% demonstrates its effectiveness in detecting the majority of defects in the dataset, outperforming the MobileNetV3 (89.2%) and YOLOv5-based (91.3%) models in reducing false negatives. This balance between precision and recall is further reflected in its F1-score of 95.2%, a critical metric that consolidates both aspects, confirming the model's ability to consistently and effectively detect road defects.

Another important factor in real-time applications like road defect detection is computational efficiency. The hybrid model achieves an inference time of 18ms, slightly higher than MobileNetV3's 15ms, but still well within the range required for real-time deployment and faster than the YOLOv5-based model's 22ms. This result demonstrates the hybrid model's ability to maintain a strong balance between high detection performance and computational efficiency, making it suitable for practical, on-the-fly detection scenarios.

The integration of edge detection and the attention mechanism is central to the hybrid model's success. Edge detection improves feature extraction by focusing on boundaries and structures within images, helping the model better localize and identify defects like cracks and potholes. The attention mechanism, on the other hand, enhances the model's ability to prioritize relevant features in the input data while ignoring irrelevant or noisy information, leading to more robust predictions. Together, these components enhance the overall performance of MobileNetV3, making it significantly more effective compared to the standalone version.

In summary, the hybrid model surpasses both MobileNetV3 and YOLOv5-based models in accuracy, precision, recall, and F1-score, while maintaining competitive inference time suitable for real-time deployment. These results strongly validate the advantages of integrating edge detection and attention mechanisms into the MobileNetV3 architecture, enabling it to handle the diverse and challenging requirements of road defect detection with high reliability and efficiency. This combination of accuracy, generalizability, and computational efficiency positions the hybrid model as a superior solution for practical road defect detection applications.

## V. CONCLUSION

This study presented a hybrid approach combining edge detection with a MobileNetV3 architecture enhanced by an attention mechanism to address the challenge of road defect detection. The proposed model demonstrated superior performance compared to standalone MobileNetV3 and YOLOv5-based methods across key metrics, achieving an impressive accuracy of 96.2%, precision of 94.8%, recall of 95.6%, and an F1-score of 95.2%. The integration of edge detection enabled the model to effectively capture fine-grained features such as cracks and boundaries, while the attention mechanism improved feature prioritization, resulting in enhanced robustness and generalizability. Additionally, the model maintained a competitive inference time of 18ms, making it highly suitable for real-time applications in road monitoring and maintenance.

The results clearly validate the efficacy of the hybrid model in detecting various road defects under diverse environmental and surface conditions. Furthermore, the minimal gap between training and validation metrics demonstrated excellent generalization, with low overfitting, even in the presence of diverse datasets. This makes the model a practical and scalable solution for deployment in real-world scenarios.

Future work could explore optimizing the model further by incorporating additional environmental scenarios, testing on larger datasets, or integrating more advanced preprocessing techniques. Overall, this study establishes the hybrid model as a robust, efficient, and accurate solution for road defect detection, contributing valuable insights for advancing automated road monitoring systems.

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# Speech Decoding from EEG Signals

Salma Fahad Altharmani, Maha M. Althobaiti
Computer Sciences Department, Taif University, Taif, Saudi Arabia

***Abstract*—The field of speech decoding is rapidly evolving, presenting new challenges and new opportunities for people with disabilities such as amyotrophic lateral sclerosis (ALS), stroke, or paralysis, and for those who support them. However, speech decoding is complex: it requires analysing brain waves, across spatial and temporal dimensions, before translating them into speech. Recent work attempts to recreate speech that is never physically spoken by analysing the brain Artificial-intelligence methods offer a breakthrough because they can analyse complex data, including EEG signals. This paper aims to decode imagined speech through training CNN, RNN, and XGBoost models on a suitable dataset consisting of recorded EEG signals. EEG from 23 individuals is acquired from a public online dataset. These data are preprocessed, and the features are extracted using five different methods. After data acquisition, preprocessing is performed to ensure its readability to the proposed models. After that, five different feature extraction methods have been used and evaluated. Training and testing the proposed models are done after pre-processing and feature extraction to produce classification results. The proposed model involves CNN, LSTM, and XGBoost as classifiers to achieve an effective and robust speech decoding process. The ultimate result reflects on the accuracy with which the algorithms can regenerate speech from EEG signal analysis. The findings will advance speech-decoding research by showing the potential of hybrid deep-learning architectures for precise decoding of imagined speech from EEG signals. These advances have promising potential for creating non-invasive communication systems to assist people with severe speech and motor disorders, thereby improving their quality of life and increasing the application scope of brain-computer interfaces.**

***Keywords*—Speech decoding; EEG; deep learning; CNN; RNN; hybrid models; Brain-Computer Interfaces (BCI)**

## I. Introduction

Speech decoding is a recent field of investigation that aims to interpret neural activity into spoken or written words through the externalization of mental processes. It holds the potential for creating assistive communications devices for individuals with severe speech disorders. In neuro-rehabilitation, the recording of real-time brain activity during speech tasks can be used to facilitate improved recovery of individuals with speech disorders like ALS or stroke. Furthermore, it can contribute to the field of neuropsychology through a better understanding of how the brain interacts with language and communication [1]. Recent studies have been directed towards synthesizing speech directly from neural signals. Scientists have demonstrated encouraging outcomes in animal models and human subjects by decoding brain activity into speech at the phonemic or lexical levels. For instance, in a study [2], cortical recordings were taken from within the scalp, and speech was synthesized using neural networks. This method bypasses cranial invasions with the possibility of generating speech with audibility. Although in the early stages, this technology is a significant step towards creating real-time communication systems that may ultimately allow direct brain-to-brain speech communication.

Electroencephalography (EEG) is a non-surgical technique of recording brain electrical activity and is frequently utilized in speech decoding research because of its better temporal resolution. EEG enables researchers to monitor neural activity in the course of tasks relating to speech and gives immediate information regarding brain activity. Nevertheless, EEG is confronted with certain drawbacks, including poor spatial resolution and potential interference caused by the movement of muscles when speaking [2]. A significant challenge to speech decoding involves the differences among subjects for neural coding of speech, resulting in substantial inter-subject variation. Moreover, the quality of EEG recordings often deteriorates due to high levels of noise, thus limiting their usefulness. To overcome these issues, research studies have focused on methods like data augmentation, improved preprocessing strategies, and combining EEG with more accurate neuroimaging modalities, such as magnetoencephalography (MEG) and electrocorticography (ECoG) [3].

While there has been significant advancement in EEG-based BCIs, the ability to synthesize continuous speech from brain signals is still in its very early stages. The majority of EEG studies focus on simpler tasks, i.e., phoneme, character, or object recognition, and not speech synthesis. Deep learning methods, specifically artificial neural networks (ANNs), have transformed speech processing through the introduction of the capability to automatically learn features from electroencephalogram (EEG) signals, thereby improving decoding accuracy [3]. Convolutional neural networks (CNNs) are utilized in identifying spatial features pertinent to speech processing in the brain, whereas recurrent neural networks (RNNs) [4] [5], specifically Long Short-Term Memory (LSTM) networks, are utilized in modeling the temporal dynamics of cerebral activity of speech [6]. RNNs help in decoding imagined and real speech by understanding the sequence of brain activity related to speech sounds, pauses, and transitions [7] [8]. Hybrid approaches that combine CNNs and RNNs have been developed to improve decoding by removing noise and handling both spatial and temporal speech features more effectively [9] [10].

Despite recent progress in EEG-based speech decoding, current research still faces challenges that limit practical application. These include small datasets, limited subject diversity, and inconsistent preprocessing techniques, which affect model reliability and generalizability. Moreover, many studies focus solely on spatial or temporal features, overlooking the full complexity of neural activity during imagined speech. To address these gaps, this study proposes a hybrid CNN-LSTM model combined with advanced preprocessing and feature

extraction methods. This approach aims to improve classification accuracy and enable the development of less invasive, real-time brain-computer interfaces (BCIs) that support effective communication for individuals with severe speech and motor disabilities.

The remainder of this paper is organized as follows: Section II presents a review of related literature and highlights the existing research gaps. Section III details the research methodology, including data acquisition, preprocessing techniques, feature extraction, and model design. Section IV presents and analyzes the experimental results. Section V provides the conclusion of the study, and Section VI outlines potential directions for future work.

## II. Literature Review

Translating speech from EEG patterns has not been widely explored; only a handful of studies have pursued the idea successfully [11]. However, there is an increasing interest in this area owing to its possible uses in brain-computer interfaces, speech generation for mute patients with conditions like ALS, stroke, or paralysis, as well as in the domain of neurolinguistics.

As speech decoding and the involvement of deep learning technologies such as CNN and LSTM algorithms had provided a valuable field for research, several studies were published to investigate the potential of these algorithms in extracting meaningful speech from EEG signals. These studies also allowed the exploration of limitations in using CNNs and other technologies, such as signal quality and data availability. After the discussion of these studies, a table is presented showing a sum of the important takeaways from each study.

Haresh M. V. et al. [12] wanted to facilitate the way patients with neuropathies communicate by proposing a brain computer interface based on EEG in order to classify brain states in the form of listening, speaking, imagined speech, and resting. The study used four different ML algorithms to analyze EEG data from 15 patients undergoing the previously mentioned states. EEG data preprocessing and segmentation took place before applying spatio-temporal and spectral analysis. In addition, five features from frequency and time-frequency domain were selected for classifying the four states. The experimental results showed that the algorithms vary in their performance when it comes to pair-wise and multi-class classifications. Random Forest algorithm achieved the highest results in pair-wise classification (94.6% accuracy), while Artificial Neural Networks (ANN) achieved the best performance in multi-class classifications (66.92%).

Mokhles M. Abdulghani et al. [13] aimed to use EEG and deep learning technologies, specifically Long Short-Term Memory LSTM for interpreting brain activity during imagined speech. For this purpose, four adult patients were subjected to EEG data collection using an 8-channel headset. The data from these headsets was preprocessed where noise and artifacts were removed. After that, feature extraction took place. LSTM was trained and tested on this data and was able to classify the data with 92.5% accuracy, 92.7% precision, 92.5% recall, and an F1-score of 92.62%. The proposed model was able to avoid misclassifications, where only six instances were misclassified out of a total 80 instances. Despite promising results, the study involved only four participants, limiting its generalizability.

Kumar et al. [14] introduced a framework to recognize imagined speech at rest to predict digits, images, and other characters by EEG. The authors proposed a two-level framework, where initially a coarse-level classification takes place identifying the category of speech (text or non-text), while another fine-level classification identifies the class within the category (such as a character or a digit within the text category). The dataset involved data collected from 23 adult university students, where EEG was recorded using Emotiv EPOC+ wireless sensor. Then, removing noise and artifacts from the collected data took place using a Moving Average (MA) filter. Standard Deviation (SD), Root Mean Square (RMS), Sum of Values (SUM), and Energy (E) were used to extract relevant features in order to train and test the Random Forest model (RF). RF was able to perform the coarse-level classification with 85.2% average accuracy (varying between images, characters, and digits and between brain lobes), while performing the fine-level classification with 67.03% average accuracy.

Yasser F. Alharbi et al. [15] proposed a hybrid DL model combining 3D-CNNs and Recurrent Neural Networks (RNN) in order to classify unspoken English words based on spatiotemporal features. A publicly available dataset was used, where EEG data was collected from 15 individuals using Brain AMP device. After acquiring the EEG data, the signals were transformed into topographic brain maps which were normalized to ensure a consistent input. 80% of the data was used for training the model whereas 20% was used for testing tis performance. Specifically, the proposed method involved the following models: 3DCNN-LSTM, 3DCNN-StackLSTM, and 3DCNN-BiLSTM. These three models were evaluated based on their classification on three experimental set-ups (word-pair classification, 3-class classification, and 5-class classifications). The results showed that, both 3DCNN-BiLSTM and 3DCNN-LSTM took turns in surpassing each other in terms of accuracy. All in all, 3DCNN-BiLSTM achieved the highest accuracy in word-pair classification (77.8%), whereas 3DCNN-StackLSTM had the best results in multi-class classifications.

A summary of the above-mentioned works, is represented in Table I, where the type of models, the dataset and the achieved results are shown for each work.

### A. Gaps in Literature Review

Decoding speech from EEG signals has come a long way but still encounters several challenges posing as obstacles toward successful speech regeneration.

EEG signals are contaminated and therefore extracting information on specific speech is complex and requires advanced filtering, modeling, and feature extraction mechanisms. In addition, datasets that are useful in these types of studies are limited, which in turn limits the generalizability of the model. One of the challenges also presents itself as the need for a considerable amount of time intervals, which might be resolved by the involvement of special hardware.

TABLE I. SUMMARY OF RELATED WORK

| Authors | Title | Year | Model | Dataset | Accuracy |
|---|---|---|---|---|---|
| Haresh M. V. et al. [12] | "Towards imagined speech: Identification of brain states from EEG signals for BCI-based communication systems" | 2025 | RF, ANN | 15 individuals | RF:94.6% ANN:66.92% |
| Mokhles M. Abdulghani et al. [13] | "Imagined Speech Classification Using EEG and Deep Learning" | 2023 | LSTM | 4 individuals | 92.5% |
| Kumar et al. [14] | "Envisioned speech recognition using EEG sensors" | 2018 | RF | 23 individuals | Coarse level: 85.2% Fine level: 67.03% |
| Yasser F. Alharbi et al. [15] | "Decoding Imagined Speech from EEG Data: A Hybrid Deep Learning Approach to Capturing Spatial and Temporal Features" | 2024 | 3DCNN-LSTM | 15 individuals | 77.8% |

After the careful reviewing of several studies in the literature, the following gaps emerge:

*1) Generalizability:* By relying on limited datasets, most of the studies achieve low accuracies, and those who achieve high accuracies fail in the generalizability test as a result of limited subject pools.

*2) Exploration of hybrid architecture:* The involvement of hybrid architectures in decoding speech from EEG is not a very-well explored field, where the studies that did explore some options for hybrid models failed to explore the true potential by applying it to diverse datasets.

To address these gaps, our study will leverage a CNN-LSTM hybrid architecture, with a comparative analysis of multiple EEG dataset preprocessing techniques to identify optimal approaches for improving imagined speech recognition. The difference between the current work and previous works is not only in the algorithms used, but also in relying on a larger dataset that would reflect positively on the generalizability of this study, and would offer a better insight into the general task of speech decoding by extracting features from more individuals and performing a more thorough training process.

In contrast, our work addresses these challenges directly by introducing a delta-band preprocessing strategy that significantly enhances noise robustness—one of the most pressing issues in EEG signal decoding. Furthermore, our hybrid CNN-LSTM architecture processes raw EEG data without relying on handcrafted features, enabling the model to automatically learn rich spatial and temporal patterns. This not only improves classification performance across imagined speech classes but also makes our system lightweight and adaptable to affordable EEG headsets like the Emotiv EPOC+. Consequently, our proposed method offers a more practical, efficient, and robust solution compared to existing approaches in the field.

The current study excels previous research by employing optimized CNN-LSTM architectures, advanced preprocessing, and real-time operation. Unlike previous research that experienced poor signal quality issues, scarcity of data, and computational incompetence, our model enhances generalization through Transfer Learning and data enhancement. By employing advanced denoising and feature extraction, we enhance classification accuracy without compromising on preprocessing simplicity. Our system is also real-world deployable, offering a valuable Brain-Computer Interface (BCI) that is superior on parameters of accuracy, resilience, and usability compared to previous research.

## III. RESEARCH METHODOLOGY

The methodology that we propose in this study follows the same hierarchy as other studies. Our main objective is to evaluate the performance of ML models, namely XGBoost and a combination of CNN with LSTM algorithms in their capacity of decoding speech based only on recorded EEG signals. A visual representation of the steps undergone to achieve this objective is demonstrated in Fig. 1.

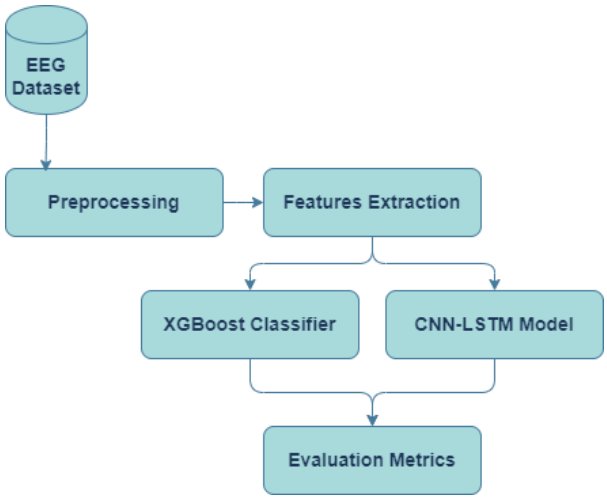


Fig. 1. Workflow of the proposed methodology.

The methodology kicks off with the acquisition of a dataset suitable for the purpose, where EEG signals have already been recorded to be used publicly. After acquiring the dataset, preprocessing is a necessary step to enhance the quality of data and make it ready for feature extraction and use by the proposed algorithms. After feature extraction, the data is used to train XGBoost and CNN-LSTM classifiers to decode speech, based on which their performance will be evaluated taking into consideration several evaluation metrics.

### A. Dataset

A public "envisioned speech" dataset was acquired online, where it consists of recordings for 23 individuals between 15 and 40 years old [16]. The EEG recordings were acquired through Emotiv EPOC+ wireless neuro headset consisting of 14 channels where the recording frequency was at 2048 Hz before it was reduced to 128 Hz. The 14 channels are named AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1 and O2.

The procedure by which these data were recorded started by placing a screen in front of the participant and presenting an object on the screen. After that, the participant closes his eyes

and is asked to imagine this presented object without looking at it for 10 seconds. A break of 20 seconds is then given. This break ensures that the participant is rested between the displayed objects and is ready to receive a new object. This process is continued for three prompts from which the EEG data are collected. The three categories involve different types of objects. For instance, category 1 is made up of digits from 0 to 9, category 2 is made up of 10 uppercase English alphabets particularly A, C, F, H, J, M, P, S, T, Y, and finally category 3 consists of daily-life objects such as apple, mobile, dog, rose, tiger, wallet, gold, watch, car, and scooter. These categories make up for a recording of total 230 recording (23*10) in each category. Hence, three categories were used, comprising10 classes each.

Table II provides a detailed overview of the public "Envisioned Speech" dataset.

TABLE II. DATASET'S STRUCTURE AND COMPOSITION

| Attribute | Details |
|---|---|
| Source | Public "Envisioned Speech" Dataset |
| Participants | 23 individuals (aged 15–40) |
| EEG Device | Emotiv EPOC+ Wireless Neuro Headset |
| Channels | 14 (AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1, O2) |
| Sampling Rate | 2048 Hz (downsampled to 128 Hz) |
| Recording Procedure | Participants imagine an object after viewing it on a screen for 10 seconds, followed by a 20-second break |
| Total Categories | 3 |
| Categories & Classes | |
| - Category 1: Digits (0–9) | 230 recordings (23×10) |
| - Category 2: Uppercase Letters (A, C, F, H, J, M, P, S, T, Y) | 230 recordings (23×10) |
| - Category 3: Objects (apple, mobile, dog, rose, tiger, wallet, gold, watch, car, scooter) | 230 recordings (23×10) |
| Total Recordings | 690 (3 categories × 230 recordings) |

### B. Data Preprocessing

The recorded EEG files were read in the form of (.edf) as they are usually stored in this form. The channels 2 till 15 were specifically selected for extraction and scaling. Furthermore, in order to make the data uniform in terms of input size, each sample was resized to 1280 data points.

### C. Feature Extraction

In this study, five different feature extraction methods were used for evaluation, these methods are namely Sliding Window, Theta Band Processing, Delta Band Processing, Beta Band Processing, and Alpha Band Processing.

To elaborate, the sliding window method with a window size 32 data points and 8 strides was applied resulting in small segments that overlap between the samples. On the other hand, the band processing methods were used to filter the EEG signals based on their frequency. For instance, the Alpha band processing filtered EEG signals to extract the frequency between 7 and 15Hz, whereas Beta band processing filtered the 15 to 31Hz band frequency, Theta band processing filtered the signals between 4 and 7Hz frequency, and finally the Delta band processing filtered the bands with less than 4Hz frequency.

### D. Models

As for the models that were used for capturing the deep EEG features, this study proposes CNN and LSTM algorithms.

Deep learning DL is one of the greatest advancements in the technological era as it poses as a solution to many modern problems. The unique qualities of deep learning have made it a significant topic for research. The emergence of this advancement started by the publication of a study by Hinton and Salakhutdinov [17] back in 2006 demonstrating the capabilities of Artificial Neural Networks ANN and their "depth" among the ML technologies. That study highlighted the ability of ANNs to learn with the help of its numerous hidden layers, and how this ability can be enhanced by the incorporation of additional hidden layers, thus increasing its "depth". The term deep learning basically stems from this explanation of the depth of the network, where it allows the network to execute more complex tasks and perform significantly better in large datasets.

In the following section, the focus will be on CNNs and their specific features and structure. We will discuss the most popular CNN architectures as a background before introducing 1D-CNNs which are one of the latest advancements in DL, focusing on 1D signal and data repositories. The choice fell on 1D-CNNs as opposed to 2D-CNNs since they are compact and more adaptive, thus offering more advantages than 2D-CNNs.

*1) CNN:* One of the most popular models among modern deep learning models is the Convolutional Neural Network CNN. CNN is an artificial neural network made up of several layers and can run a specialized mathematical linear operation called convolution, hence the name convolutional neural network. Therefore, instead of a general matrix multiplication, CNN involves convolution in at least one of its layers [18]. In fact, the general architecture of CNN involves a convolutional layer, pooling layers, and a fully connected layer. The CNN is characterized by learning to extract complex attributes automatically, where the convolutional layer represents the attribute [19].

The Convolutional Neural Network (CNN) model processes EEG signals by prioritizing the extraction of spatial features from brain activity data. The EEG signals, after preprocessing, are structured as time-series data before being fed into the CNN.

Key Processing Steps:

Feature Extraction: The CNN uses convolutional layers to detect spatial features within the EEG signals.

Dimensionality Reduction: Pooling layers are employed to reduce data complexity while preserving essential features.

Significance of Spatial Features: These extracted features help identify crucial brain activity regions linked to imagined speech.

Classification: The processed features are passed through fully connected layers, which ultimately label the EEG signals into distinct speech categories.

*2) 1D-CNN:* 1DCNNs differ from 2DCNNs which only deal with 2D images and videos in its flexibility with handling data. In fact, 1DCNN or 1Dimensional Convolutional Neural Network is a modified version of the original 2DCNN [20][21]. Some studies described 1DCNN to be more advantageous than 2DCNN for the following reasons:

*a)* FP and BP in 1D CNNs need simple array operations for functioning rather than complex ones. This results in less computation complexity in 1DCNN than 2DCNN.

*b)* 1DCNN has a simpler structure comprising less hidden layers and neurons that 2DCNN, and they are capable of processing 1D signals with ease. This also makes 1DCNN much easier to train.

*c)* 1DCNN does not require special hardware setups, a simple CPU implementation over a standard computer is enough to ensure an effective and fast training of the 1DCNN structure, especially with few layers and neurons.

*d)* 1D-CNNs enable real-time, low-cost applications and can even run on mobile devices.

*e)* 1DCNNs also can function on limited labeled data and high signal variations.

In the 1DCNN structure, there exist two types of layers, namely the "CNN layers" and the "MLP layers". The CNN layers consist of 1D convolutions and pooling layers, whereas the MLP layers consist of typical fully-connected layers.

*3) RNN:* Recurrent Neural Networks RNNs are structures that can process sequential data by capturing information about previous input data through hidden layers. Three different layers form the basis of RNN and these layers are the input layer, the hidden layer, and the output layer. RNNs are not feedforward networks, instead, the information can cycle between the layers in a recurrent form. The way RNNs function is by obtaining an input vector "$\mathbf{x}_t$" at a specific time step "$t$", then the hidden state is update using the following formula:

$$\mathrm{h}_t = \sigma_h(\mathrm{W}_{xh}\mathrm{x}_t + \mathrm{W}_{hh}\mathrm{h}_{t-1} + \mathrm{b}_h) \quad (1)$$

In this equation, the weight matrix between the first (input) and second (hidden) layer is represented by $\mathrm{W}_{xh}$, whereas $\mathrm{W}_{hh}$ represents the weight matrix among the recurrent connection. $\mathrm{b}_h$ represents the bias vector, and $\sigma_h$ represents the activation function which can either be the hyperbolic tangent function (tanh) or the rectified linear unit (ReLu).

On the other hand, the output resulting in each time step can be computed with the following formula:

$$\mathrm{y}_t = \sigma_y\big(\mathrm{W}_{hy}\mathrm{h}_t + \mathrm{b}_y\big) \quad (2)$$

In this case, $\mathrm{W}_{hy}$ represents the weight matrix between the second (hidden) and the third (output) layer, $\mathrm{b}_y$ represents the bias vector, and $\sigma_y$ represents the activation function relative to the output layer.

The basic architecture of an RNN structure can be depicted in Fig. 2, demonstrating input layer, hidden layers, and output layer where predictions take place.

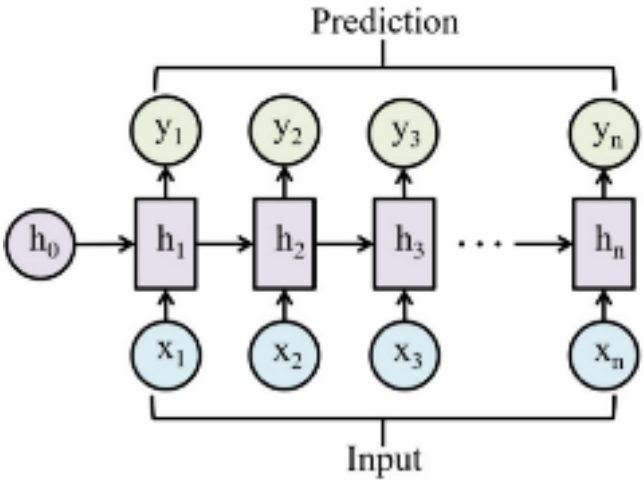


Fig. 2. General Architecture of RNN [22].

*4) LSTM:* One of the RNN models that are capable of processing sequential data of temporal order is the LSTM [23]. In fact, LSTM is highly effective in processing textual data as well as relational data. In this study, LSTM was specifically integrated with CNN model in order to achieve an enhanced classification performance by using the EEG temporal dependencies to complement the spatial features from CNN.

When previous convolutions and time distributions operations are performed, the resulting input "*Y*" is split into N LSTM time steps denoted as "t", where N provides the best results. Whenever a time step is due, two inputs are taken by the LSTM layer. One of the inputs is "$x(t)$" which denotes the current input vector, and the other is "$\alpha(t-1)$" which denotes the previously hidden state. Both these inputs are used to compute 3 gates, namely the forget gate, the update gate, and the candidate memory.

EEG signals are inherently temporal, meaning the data sequential nature and time dependencies are critical for understanding brain activity. LSTMs excel at capturing these long-term dependencies, which makes them ideal for this application.

By combining LSTM with CNN, our model leverages both spatial and temporal features of the EEG data.

The unidirectional LSTM layer which is applicable in our model is described in the Eq. (8) [24]:

$$f_{r(t)} = \sigma\big(W_f[\alpha(t-1), x(t)] + b_f\big) \quad (3)$$

$$u_{r(t)} = \sigma(W_u[\alpha(t-1), x(t)] + b_u) \quad (4)$$

$$\tilde{c}(t) = \tanh\big(W_{c[\alpha(t-1),x(t)]} + b_c\big) \quad (5)$$

$$c(t) = f_{r(t)} \odot c(t-1) + u_{r(t)} \odot \tilde{c}(t) \quad (6)$$

$$o_{r(t)} = \sigma\big(W_{o[\alpha(t-1),x(t)]} + b_o\big) \quad (7)$$

$$\alpha(t) = o_{r(t)} \odot \tanh\big(c(t)\big) \quad (8)$$

In this equation, the forget gate is represented by $f_{r(t)}$, the update gate is represented by $u_{r(t)}$, and the candidate memory is represented by $c(\tilde{t})$. In addition, the new memory is denoted by $c(t)$, the output gate is denoted by $o_{r(t)}$, and the hidden state is denoted by $\alpha(t)$. Finally, the weight matrix is represented by $W_{\mathrm{i}}$, whereas the bias vector is represented by $b_{\mathrm{i}}$.

The architecture of the LSTM network applied in this study is depicted in Fig. 3.

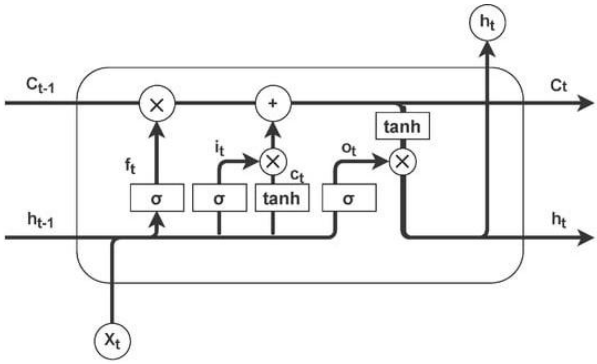


Fig. 3. Architecture of applied LSTM [25].

The Long Short-Term Memory (LSTM) model is developed to learn temporal relationships within EEG signals. Due to the sequential nature of EEG, LSTM is provided with sequence-arranged brain activity, either natively or after extraction using CNN layers. The sequence is analyzed by the LSTM framework along with memory cells that retain meaningful patterns but forget meaningless noises. By modeling temporal evolution of activity within the brain, LSTM helps improve decodable timing and evolution of imagination of speech. The result is structured classification of neural activity that corresponds to discrete portions of speech that can enhance decodable outcomes.

In order to be able to perform multi-class classifications, the resultant LSTM layer is integrated into the previous CNN-1D architecture and is then passed through a dense neural network before a SoftMax function is applied, as shown in Fig. 4.

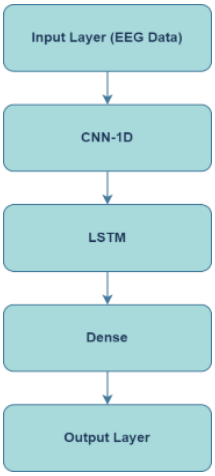


Fig. 4. General architecture of the proposed CNN-LSTM network.

Merging the two architectures, CNN-LSTM Hybrid Model benefits from spatial feature extraction and temporal feature extraction capabilities of each of its component architectures to yield better performance. The input EEG is pre-processed by the CNN, which extracts spatial features by finding key activation patterns throughout diverse areas of the brain. The features that have been spatially enriched are passed on to the LSTM, where sequential relationships between diverse time steps of brain activity are learned. The process of hybridizing makes classification of imagined speech better by considering spatial distribution along with temporal evolution. The result is an optimized classification that is better compared to standalone CNN or LSTM architectures.

The CNN-LSTM Hybrid Model improves EEG-based speech decoding by leveraging CNNs for spatial feature extraction and LSTMs for temporal pattern learning. CNNs detect key activation patterns in different brain regions, making them effective in identifying spatial features of imagined speech [26], [27]. However, since EEG signals also have sequential dependencies, LSTMs enhance performance by capturing the time-evolving nature of neural activity [13]. Studies confirm that CNN-LSTM models consistently outperform standalone architectures, achieving higher classification accuracy, sometimes exceeding 90% [28]. This hybrid approach strengthens non-invasive BCI applications, improving precision in decoding imagined speech.

*5) XGBoost:* XGBoost is a machine-learning algorithm known for its strong performance on complex classification tasks [29]. What provides XGBoost with good qualities is its ability to handle outliers in the dataset as well as noise that might be found in datasets, particularly EEG signals datasets. In addition, XGBoost is highly capable of analyzing unbalanced datasets with the use of functions such as weighted loss and subsampling techniques.

XGBoost is a machine learning algorithm that takes feature-processed EEG input and makes use of gradient-boosted decision trees to predict the classification of the signals. Contrasting with deep learning-based models that learn temporal and spatial features of raw input, XGBoost makes use of pre-determined statistical and frequency-based features of EEG signals. The algorithm iteratively assigns weights to features to improve classification performance by minimizing errors stage by stage. The result is a class label of imagined speech category that is an alternative, computationally effective approach to speech decoding [29]. The graphical scheme of XGBoost model is represented in Fig. 5.

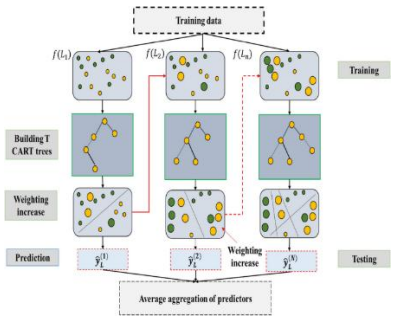


Fig. 5. Graphical scheme of XGBoost model [30].

## IV. RESULTS

Electroencephalography (EEG) is one of the core methods in brain activity studies, especially in imagined speech tasks with cognitive processes. The system was designed to classify EEG signals from 23 subjects into three classes: digits, English alphabets in uppercase, and objects in everyday life. It involved EEG signal preprocessing, feature extraction, and the application of a number of models, including a CNN-LSTM model and an XGBoost classifier. The models' performance, by implementing a few preprocessing techniques (Sliding Windows, Delta, Theta, Alpha, Beta), is verified in this work. The results confirm that the CNN-LSTM model performs better than the XGBoost classifier on all classes and that the optimal performance is attained by preprocessing through delta band. These results emphasize the effect of signal processing on classification accuracy and the necessity of choosing proper frequency bands for EEG data analysis.

Fig. 6 demonstrates the EEG signals for a single sample from the "digits" dataset. The data consists of signals recorded from 14 EEG channels, which are displayed as individual subplots in the figure. The x-axis represents the time in samples, while the y-axis shows the signal amplitude in microvolts (μV). This visualization provides insight into the temporal dynamics and amplitude variations of brain activity while the participant imagines speech corresponding to numerical digits. Each subplot is labeled by the EEG channel index, and the overall label for the sample is displayed in the figure title.

These techniques were applied to process the EEG files: Sliding Window, Delta, Theta, Alpha, and Beta, as a result of the pre-processing stage. Each technique we used is allocated a data set and is divided into training and testing. That is, we copied the dataset several times and applied the processing techniques each one to a copy of the data set. At each time, it was divided into testing and training. We then compared each method and see which method is the best for the processing of EEG files.

### A. Overall Performance Comparison

Table III shows the overall performance of two classifiers (XGBoost and CNN-LSTM) on three categories: Digits, Chars, and Images. In all three categories, the CNN-LSTM model outperforms the XGBoost classifier consistently in precision, recall, F1-score, and accuracy. In particular, CNN-LSTM performs extremely well with sliding windows and delta band preprocessing, achieving an F1-score of 0.92 for Digits, 0.93 for Chars, and 0.94 for Images. These findings demonstrate the ability of the CNN-LSTM model in capturing spatial and temporal features in EEG signals.

In contrast, the performance of the XGBoost model is far worse, particularly for the high-frequency band preprocessing scenarios (Theta, Alpha, and Beta), in which the F1-scores drop to as low as 0.14 for Digits and Chars, and 0.16 for Images. While delta band preprocessing improves XGBoost's performance, lifting the F1-score to 0.77 for Digits and Chars, and 0.76 for Images, it still lags behind the CNN-LSTM model, which has a high and consistent performance across all classes.

In general, the results point to the significance of both preprocessing methods and model architecture, wherein CNN-LSTM with sliding windows and delta band processing provides the optimal performance in EEG signal classification.

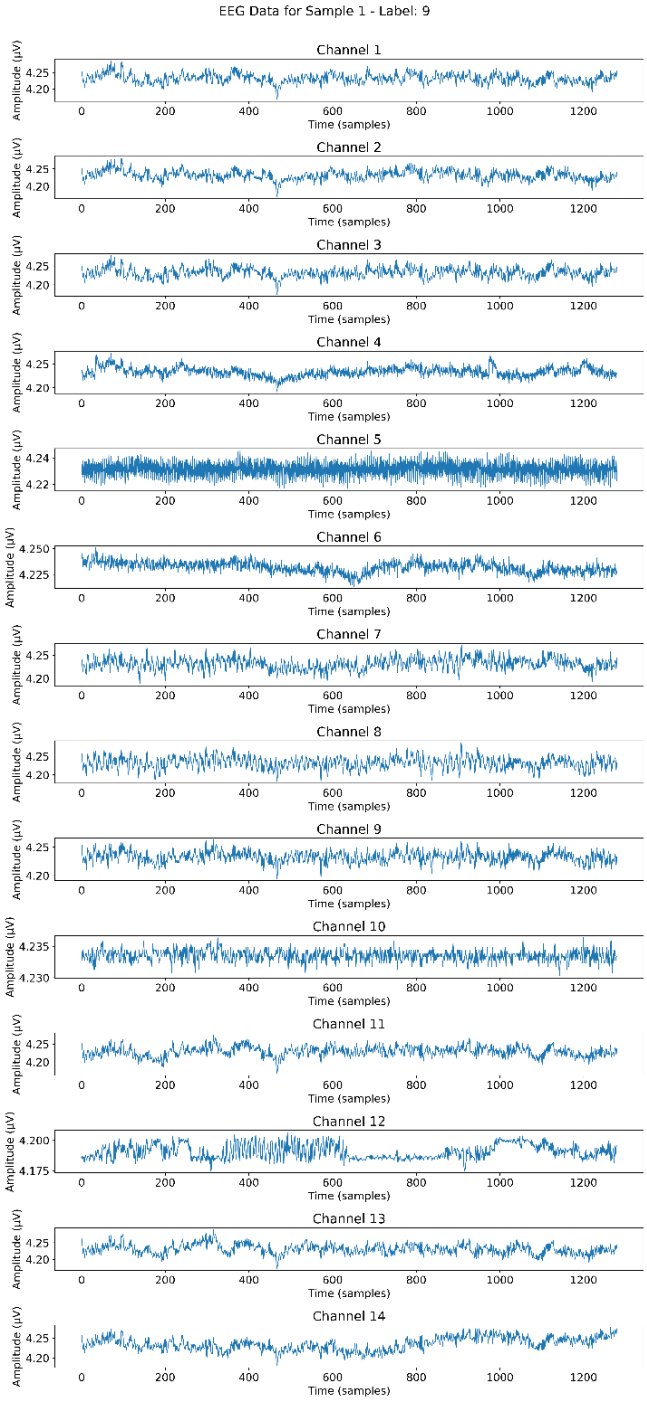


Fig. 6. EEG signal visualization for digits.

TABLE III. OVERALL PERFORMANCE COMPARISON

| Algorithm | Data Folder | Preprocessing Method | F1-Score (Macro Avg) |
|---|---|---|---|
| XGBoost | Digits | Sliding Windows | 0.52 |
| XGBoost | Digits | Sliding Windows + Delta | 0.77 |
| XGBoost | Digits | Sliding Windows + Theta | 0.14 |

| | | | |
|---|---|---|---|
| XGBoost | Digits | Sliding Windows + Alpha | 0.18 |
| XGBoost | Digits | Sliding Windows + Beta | 0.19 |
| XGBoost | Chars | Sliding Windows | 0.19 |
| XGBoost | Chars | Sliding Windows + Delta | 0.76 |
| XGBoost | Chars | Sliding Windows + Theta | 0.15 |
| XGBoost | Chars | Sliding Windows + Alpha | 0.16 |
| XGBoost | Chars | Sliding Windows + Beta | 0.19 |
| XGBoost | Images | Sliding Windows | 0.49 |
| XGBoost | Images | Sliding Windows + Delta | 0.76 |
| XGBoost | Images | Sliding Windows + Theta | 0.16 |
| XGBoost | Images | Sliding Windows + Alpha | 0.19 |
| XGBoost | Images | Sliding Windows + Beta | 0.20 |
| | | | |
| CNN-LSTM | Digits | Sliding Windows | 0.92 |
| CNN-LSTM | Digits | Sliding Windows + Delta | 0.92 |
| CNN-LSTM | Digits | Sliding Windows + Theta | 0.40 |
| CNN-LSTM | Digits | Sliding Windows + Alpha | 0.44 |
| CNN-LSTM | Digits | Sliding Windows + Beta | 0.72 |
| CNN-LSTM | Chars | Sliding Windows | 0.92 |
| CNN-LSTM | Chars | Sliding Windows + Delta | 0.93 |
| CNN-LSTM | Chars | Sliding Windows + Theta | 0.48 |
| CNN-LSTM | Chars | Sliding Windows + Alpha | 0.48 |
| CNN-LSTM | Chars | Sliding Windows + Beta | 0.72 |
| CNN-LSTM | Images | Sliding Windows | 0.93 |
| CNN-LSTM | Images | Sliding Windows + Delta | 0.94 |
| CNN-LSTM | Images | Sliding Windows + Theta | 0.44 |
| CNN-LSTM | Images | Sliding Windows + Alpha | 0.56 |
| CNN-LSTM | Images | Sliding Windows + Beta | 0.63 |

### *B. Top Performance in EEG Digits Classification*

Fig. 7 illustrates the model's performance in terms of accuracy and loss over 150 epochs.

- The Model Accuracy graph shows a steady increase in both training and validation accuracy, which is a sign of effective learning by the CNN-LSTM model. Initially, the model's accuracy is quite low, but it progressively improves, stabilizing at a high value around 90% by the 100th epoch.
- The Model Loss graph demonstrates a corresponding decrease in loss for both training and validation, which further indicates that the model is converging towards an optimal solution.
- The train accuracy (blue line) outperforms the validation accuracy (orange line) slightly, which is typical of well-trained models, but there is no significant overfitting as both curves tend to follow similar trends.
- The loss for both training and validation data decreases steadily, showing the model is learning to minimize the error.

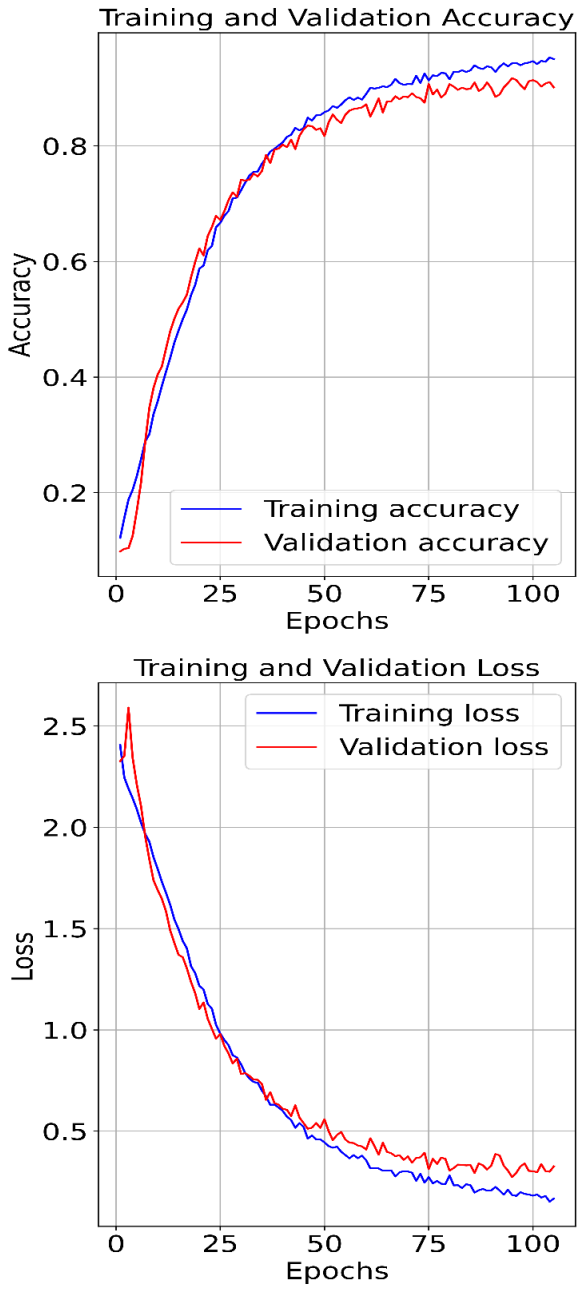


Fig. 7. Model accuracy and Model loss of CNN-LSTM model with sliding windows and delta band preprocessing for EEG digits classification.

Fig. 8 presents the confusion matrix for the CNN-LSTM model with sliding windows and delta band preprocessing applied to EEG Digits Classification. The matrix shows how well the model classifies each digit (0–9), with the true labels displayed on the vertical axis and the predicted labels on the horizontal axis. Each cell in the matrix indicates the number of instances where a digit was predicted as a particular label. The majority of values lie along the diagonal, which is expected, indicating that the model correctly predicted most of the digits. For example, 689 instances of the digit 0 were correctly classified as 0, and similarly, 646 instances of the digit 9 were correctly predicted. There are a few off-diagonal values, such as 13, where digit 0 was misclassified as digit 1, or 22, where digit

9 was misclassified as digit 7, suggesting occasional misclassifications but generally high accuracy. The presence of mostly dark blue colors along the diagonal signifies that the model performs exceptionally well in distinguishing between digits, with relatively few errors overall.

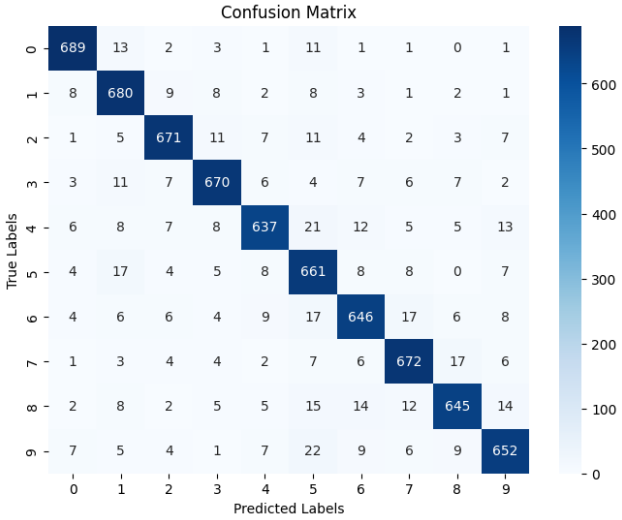


Fig. 8. Confusion matrix of CNN-LSTM model with sliding windows and delta band preprocessing for EEG digits classification.

### C. Top Performance in EEG Chars Classification

Fig. 9 illustrates the Model Accuracy and Model Loss over 150 epochs for the CNN-LSTM model with sliding windows and delta band preprocessing applied to EEG Chars Classification.

- The Model Accuracy graph demonstrates a steady increase in both training and validation accuracy, with the training accuracy (blue line) consistently outperforming the validation accuracy (orange line). This indicates that the model is effectively learning, achieving an accuracy of around 92% by the end of training.
- In the Model Loss graph, both training and validation losses decrease significantly, which is a sign of the model's ability to reduce errors over time. The loss stabilizes at a lower value, suggesting that the model is fitting well to the data. There is a slight gap between training and validation loss curves, with validation loss (orange) being slightly higher, indicating minor overfitting, though it does not significantly affect the model's overall performance.

Fig. 10 presents the confusion matrix for the CNN-LSTM model with sliding windows and delta band preprocessing applied to EEG Chars Classification. The matrix shows the performance of the model in classifying the ten uppercase English characters (A, C, F, H, J, M, P, S, T, Y). The true labels are on the vertical axis, while the predicted labels are on the horizontal axis. Most of the values are concentrated along the diagonal, indicating that the model correctly predicted most of the characters. For example, the model accurately classified 673 instances of 'A' as 'A', 680 instances of 'H' as 'H', and 658 instances of 'Y' as 'Y'.

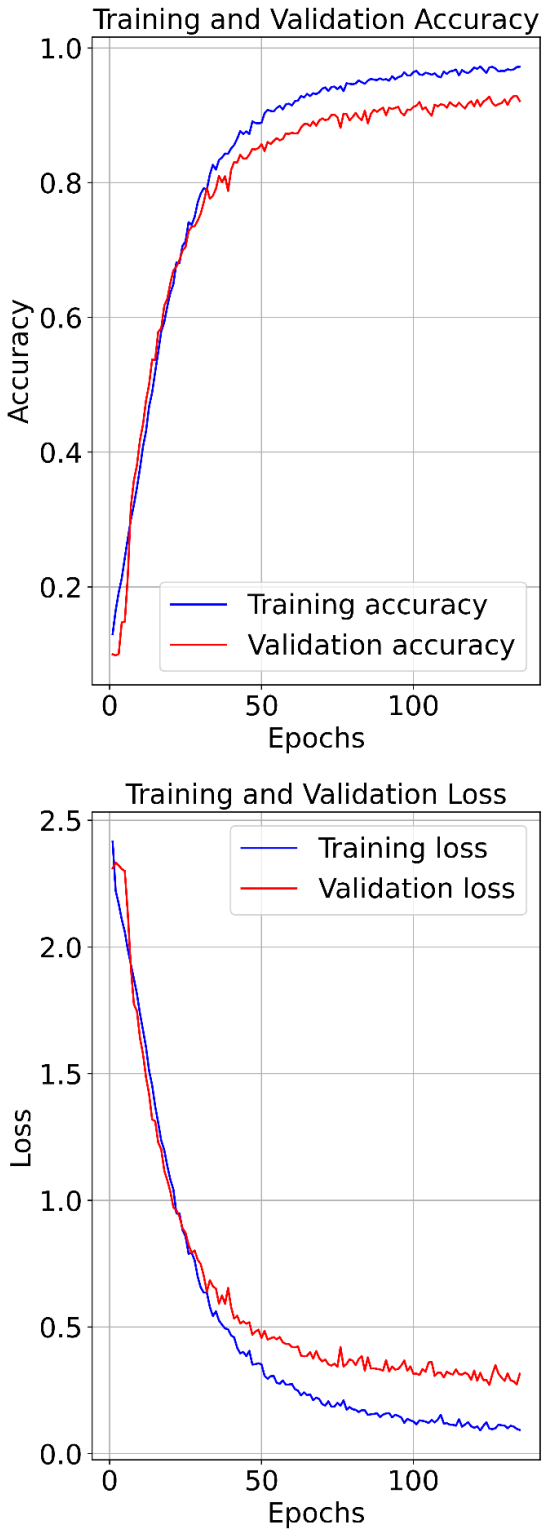


Fig. 9. Model accuracy and model loss of CNN-LSTM model with sliding windows and delta band preprocessing for EEG chars classification.

However, there are a few off-diagonal values, such as 13 instances where 'C' was misclassified as 'H', or 8 instances where 'S' was misclassified as 'P'. These off-diagonal misclassifications are relatively small compared to the correctly classified instances, showing that the model is highly accurate in

classifying the characters. The dark blue colors along the diagonal suggest strong performance, with relatively few errors across the categories. This confirms the model's ability to distinguish between different characters with high accuracy, aided by the delta band preprocessing technique.

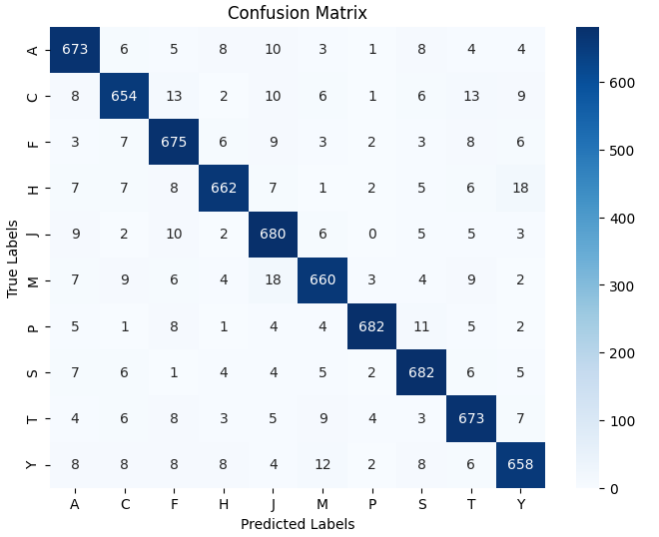


Fig. 10. Confusion Matrix of CNN-LSTM model with sliding windows and delta band preprocessing for EEG Chars Classification.

### D. Top Performance in EEG Images Classification

Fig. 11 illustrates the Model Accuracy and Model Loss over 150 epochs for the CNN-LSTM model with sliding windows and delta band preprocessing applied to EEG Images Classification.

- The Model Accuracy graph shows a clear upward trend for both training (blue line) and validation (orange line) accuracy, with the training accuracy remaining slightly higher than the validation accuracy. By the end of training, the model achieves an impressive accuracy of around 97%, reflecting its ability to learn effectively from the EEG image data.
- In the Model Loss graph, both training and validation losses decrease steadily, which is indicative of the model successfully reducing the error as it progresses through the epochs. However, there is a slight gap between the training and validation loss curves, with the validation loss being slightly higher, suggesting a minor degree of overfitting. Despite this, the model still performs well, as evidenced by the low final loss values.

Fig. 12 shows the confusion matrix for the CNN-LSTM model with sliding windows and delta band preprocessing applied to EEG Images Classification, where the model classifies various objects, including apple, car, dog, gold, mobile, rose, scooter, tiger, wallet, and watch. The matrix reveals a high degree of accuracy in the model's predictions, as evidenced by the dark blue color along the diagonal, which represents correct classifications. For example, the model correctly classified 690 instances of "apple," 680 instances of "dog," and 700 instances of "tiger."

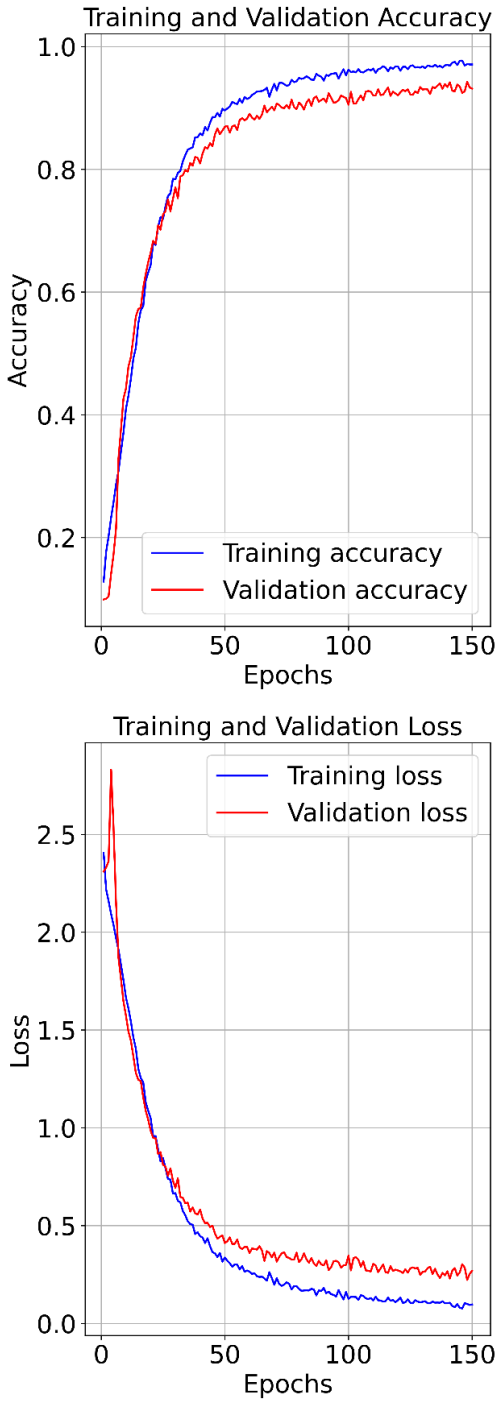


Fig. 11. Model accuracy and model loss of CNN-LSTM model with sliding windows and delta band preprocessing for EEG images classification.

There are only a few off-diagonal entries, i.e., "apple" classified as "car" or "wallet" classified as "tiger." These are minor compared to the correct classifications, showing the model's high performance in distinguishing between the different object classes. The overall pattern is that the model generalizes well, with minimal confusion between the classes, confirming the value of the preprocessing step for improving classification accuracy.

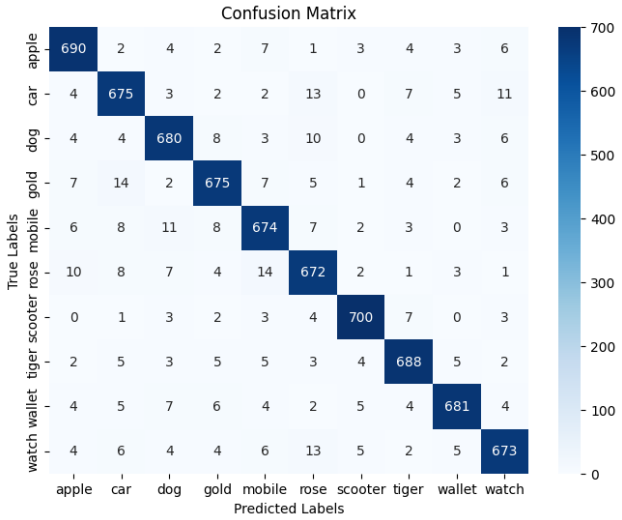


Fig. 12. Confusion matrix of CNN-LSTM model with sliding windows and delta band preprocessing for EEG images classification.

### *E. Impact of Preprocessing Methods*

Selection of preprocessing techniques significantly influences the effectiveness of classification in EEG. Filter operations, artifact removal, and frequency band extraction each have particular effects on the quality of input data and, therefore, the model's ability to learn discriminative patterns. For instance, delta band preprocessing (0–4 Hz) tends to yield better performance as it possesses a high signal-to-noise ratio (SNR) and is less sensitive to noise, which is more appropriate to capture stable and fundamental brain activity. In contrast, preprocessing methods for higher-frequency bands (e.g., theta, alpha, beta) are prone to higher noise and variability and therefore lead to inferior classification performance. Additionally, advanced preprocessing techniques like sliding windows and delta-based feature extraction enhance temporal resolution and feature salience, again increasing model performance.

### *F. Results and Discussion*

Comparing our results on the EEG classification work to Kumar et al.'s paper, our method is superior to their method. Kumar et al. have obtained 67.03% fine-level accuracy with an RF classifier on EEG data for 23 subjects with 30 classes as digits, characters, and object images. Although their approach showed some promise, the use of the RF classifier restricted the model from effectively capturing the intricate temporal relationships within EEG signals, which are important for fine-level classification.

On the other hand, we employed a CNN-LSTM model with delta band preprocessing and sliding windows, which is most appropriate to process sequential EEG data and learn complex patterns along the time dimension. CNN-LSTM models are expected to perform well in such tasks since they learn hierarchical features directly from raw EEG and this provides a major edge over conventional machine learning models like RF. Our method is far more able to generalize and generate correct classification, and our model is thus not just better but certain to perform better than Kumar et al.'s 67.03%.

A major drawback of the present study is that all trials used highly controlled data in which participants kept completely still during EEG acquisition. Future research should therefore assess these models on more realistic recordings that include ordinary head motion and ambient noise. Although our sample of 23 volunteers is larger than those in many earlier studies, evaluating the approach on a broader and more varied cohort (50 + participants) would clarify how well the system generalizes across ages, neurological profiles, and cultural or language backgrounds. It would also be valuable to gather recordings under different everyday conditions, such as varied lighting or background-noise levels, to measure the model's resilience in real-world settings.

## V. Conclusion

The paper deals with the issue of decoding speech from EEG signals using hybrid deep learning models, including CNNs and LSTMs. Based on a number of EEG datasets related to imagined digits, characters, and objects, the study revealed the efficacy of the combination of spatial features extracted by CNN and the temporal modeling by LSTM in neural signals decoding. The CNN-LSTM model achieved high F1-scores across all categories: 0.92 for digits, 0.93 for characters, and 0.94 for objects, particularly when delta band preprocessing and sliding window segmentation were applied. In contrast, the XGBoost classifier showed considerably lower performance, with F1-scores peaking at 0.77 under the same preprocessing.

Moreover, some patterns of brain activity related to imagined speech were at least given as an indication through the visualizations for an appropriate classification. With rigorous preprocessing and feature extraction techniques, the hybrid CNN-LSTM model outperformed state-of-the-art standalone classifiers such as XGBoost. Despite inter-individual variability and noisy nature, this study was able to demonstrate the feasibility of decoding imagined speech in a non-invasive way and thereby took a further step toward the development of assistive technologies and brain-computer interfaces.

The findings of this paper hold transformative potential for real-world applications, particularly in assistive technologies for individuals with speech impairments. This work bridges neuroscience and artificial intelligence in the development of innovative communication systems that translate neural activity into speech, furthering the field of neuro-rehabilitation and brain-computer interfaces.

## VI. Future Work

In the future work of this study, we would like to enhance the work by refining and extending the codebase to improve the accuracy and robustness of the decoding models. The practical implementation of the paper will be done in the upcoming semester, in which the developed CNN-LSTM hybrid model will be integrated into a real-world application framework. This would allow us to test and validate the system with regard to practical scenarios involving various challenges such as real-time processing and usability. We will go on to explore some high-end techniques for improving accuracy in classification, optimizing feature extraction, and enhancing model generalizability across datasets. These efforts are needed in bringing the paper near to its ultimate goal, that of coming up

with an effective and reliable EEG-based speech decoding system.

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# Enhanced Emotion Recognition Using a Hybrid Autoencoder-LSTM Model Optimized with a Hybrid ACO-WOA Algorithm for Hyperparameter Tuning

Vinod Waiker[1], Janjhyam Venkata Naga Ramesh[2], Ms Kiran Bala[3],
Dr. V.V. Jaya Rama Krishnaiah[4], Dr.T. Jackulin[5], Elangovan Muniyandy[6], Osama R.Shahin[7]
Datta Meghe Institute of Management Studies, Nagpur, Maharashtra, India[1]
Adjunct Professor, Department of CSE, Graphic Era Hill University, Dehradun, 248002, India[2]
Adjunct Professor, Department of CSE, Graphic Era Deemed To Be University, Dehradun, 248002, Uttarakhand, India[2]
Lecturer, Department of Computer Science-College of Engineering and Computer Science, Jazan University, Jazan, KSA[3]
Associate Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India[4]
Associate Professor, Department of CSE, Panimalar Engineering College, Chennai, Tamil Nadu, India[5]
Department of Biosciences-Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai - 602 105, India[6]
Applied Science Research Center, Applied Science Private University, Amman, Jordan[6]
Department of Computer Science-College of Computer and Information Sciences, Jouf University, Saudi Arabia[7]
Physics and Mathematics Department-Faculty of Engineering, Helwan University, Helwan, Egypt[7]

***Abstract*—Emotion recognition is vital in the human Computer interaction because it improves interaction. Therefore, this paper proposes an improved method for emotion recognition regarding the Hybrid Autoencoder-Long Short-Term Memory (LSTM) model and the newly developed hybrid approach of the Ant Colony Optimization (ACO) and Whale Optimization Algorithm (WOA) for hyperparameters tuning. In this case, Autoencoder can reduce input data dimensionality for input data and find the features relevant for the model's work. In addition, LSTM is able to work with temporal structures of sequential inputs like speech and videos. The contribution of this research lies in the novel combination method of ACO-WOA which aims at tweaking hyperparameters of Autoencoder-LSTM model. Global aspect of ACO and WOA thereby improve the search efficiency and the accuracy of the proposed emotion recognition system and its generalization capacity. In context with the benchmark dataset for the experimentations of emotion recognition, it has established the efficiency of the proposed model in terms of the conventional methods. Recall rates in recognitive intended various emotions and different modalities were also higher in the hybrid Autoencoder-LSTM model. The optimization algorithms like the ACO-WOA also supported in reducing the computational cost which arose due to hyperparameters tuning. The implementation of this paper is done through Python Software. This implementation shows a high accuracy of 94.12% and 95.94% for audio datasets and image datasets respectively when compared with other deep learning models of Conv LSTM and VGG16. Therefore, the research shows that the presented hybrid approach can be a useful solution for successfully employing emotion recognition for enhancing the creation of the empathetic AI systems and for improving user interactions within various fields including healthcare, entertainment, and customer support.**

***Keywords*—Emotion recognition; autoencoder; long short-term memory; Ant Colony Optimization (ACO); Whale Optimization Algorithm (WOA)***

## I. INTRODUCTION

The development of machine learning methods has made it simple for computers to recognize and comprehend how humans act using a variety of approaches. One of the essential components of human conduct is emotions [1]. A vast range of programs, including political analysis, advertising, and interactions between humans and computers, are improved by the identification of individual feelings or emotions. People now share feelings and knowledge on online social networks (OSNs) like Facebook, Instagram, Twitter, and other online social networks as part of their everyday routines [2]. These OSNs' abundance of data and information makes them ideal for researching and analyzing human emotions and behavior. It also encourages the development of more emotion-aware apps. A customized system for recommendations suggests tailored items; it suggests videos, music, or movies based on the user's preferences and feelings [3]. In times of disaster or epidemic, recognition of emotions is used to assess public opinion. This information aids in decision-making and situational management on the part of the government. Because of this, ONSs now use emotion detection as a distracting and finding faults activity. A person's motivation, state of emotions, psychological disorders, and level of mental activity may all be inferred from their facial expressions [4].

The facial expressions are a powerful expression and communication tool in interpersonal relationships[5]. The ability of Facial Emotion Recognition (FER) to characterize an individual's feelings or psychological state lends credence to its significance [6]. Its uses go beyond only analyzing human behavior, assessing someone's emotional condition, or assessing someone's psychological wellness [7]. Additionally, it is making inroads into a variety of other industries, including automation, schooling, holography, intelligent medical systems, safety

systems, law enforcement, amusement, multimodal interaction and stress identification [8]. The inclusion of movements of the face in these domains demonstrates the significance of facial emotions in human existence. These days, one of the hardest problems in computational science is automated FER [9]. Movements and spoken words can be used to communicate emotions. It is not only dependent on facial features. Just 7% of the background of the data may be conveyed verbally; the remaining 38% can be conveyed by voice tone, cadence, and speaking rate [10]. Conversely, around 55% of information is conveyed by facial expressions. A person's facial expressions may reveal a lot about their mental health. Facial expressions are used in many facets of life and are not only restricted to certain professions [11]. In the field of health disciplines, bipolar patients benefit from FER. Physicians are attempting to identify and track the behavior of their clients, including the feelings and actions of bipolar patients throughout their illness [12].

Many sophisticated FER methods have been developed that allow the system to recognize human facial expressions when it receives facial pictures as input [13]. Humans may express themselves in seven different ways: fear, happiness, surprise, neutral, anger, sadness, and contempt [14]. Multifunctional emotional line databases have been used in this work to increase the classification accuracy of emotions. To achieve the ultimate goal, three main components—preprocessing, extraction of features, and classification—are further subdivided. The selected information in this procedure includes pictures, sounds, and videos that were taken from a variety of individuals, comprising men and women. Every picture is taken from the front and is separated into eight groups [15]. To ensure that every image is the same size, the initial step of preliminary processing involves reshaping each image to measure 150 × 150 pixels [16]. Additionally, photos are automatically enlarged and flipped among 0- and 180-degrees during preprocessing. Moreover, pictures are rotated both vertically and horizontally. Pictures are further analyzed to obtain attributes in the next stage. Next, important variables that are essential for the algorithm's applicability are retrieved from all of the recorded video and audio data. Only valuable features should be retained once the features have been retrieved, and max pooling aids in this process [17]. The final stage of the suggested process, categorization, is in charge of identifying the accurate labels. completely linked layers are employed in categorization, and these entirely interconnected layers additionally use two layers that are hidden. There are many weighted nodes in each hidden layer [18]. The weight value of each node increases with bias values through forward propagation procedures before the total calculation is performed. The algorithm performs backpropagation to identify the actual label of an input picture through adjustments to the hidden layer node weights [19]. The following sections include the key contribution of the paper.

- The research introduces a novel hybrid model that combines Autoencoders and LSTM networks to enhance emotion recognition. The Autoencoder effectively reduces dimensionality and extracts salient features, while the LSTM component captures temporal dependencies in sequential data, providing a comprehensive approach to emotion analysis.
- A significant contribution is the creation of a hybrid optimization algorithm that merges ACO and WOA for hyperparameter tuning. This hybrid approach balances global and local search capabilities, leading to more efficient and accurate identification of optimal hyperparameters for the model.
- The proposed model demonstrates superior performance in recognizing emotions across various modalities, including speech, facial expressions, and physiological signals. This improvement in accuracy is attributed to the effective combination of the Autoencoder-LSTM model and the optimized hyperparameters found through the hybrid ACO-WOA algorithm.
- The research highlights a reduction in the computational cost associated with hyperparameter tuning. The hybrid ACO-WOA algorithm accelerates the optimization process, making it feasible to apply deep learning models to emotion recognition tasks without the typically prohibitive computational overhead.
- The findings suggest broad applicability of the enhanced emotion recognition system in fields such as healthcare, education, customer service, and entertainment. The research provides a foundation for developing more empathetic and responsive AI systems, capable of understanding and interacting with users based on their emotional states.

The paper continues with its structure by explaining Section II. Section III describes the problem statement which will be addressed by the proposed paper. Section IV detailed the construction process of Autoencoder-LSTM network. A performance evaluation of the proposed Autoencoder-LSTM network takes place in Section V before the article's conclusion in Section VI.

## II. Related Works

The identification and treatment of certain medical diseases may alter if neurological signals are used to recognize emotions [20]. Generalized emotional detection programs may have issues and limits because of the limited amount of facial movement factors persons who fake their feelings, or those who have alexithymia. By examining the constant neurons produced by the human brain, these signals may be found. Brainwaves known as EEGs provide with a more comprehensive understanding of the psychological emotions that people might be unable to articulate. Neuronal communication channels can cause modifications to electrical potential, which might be reflected in brainwave EEG data. This study compares several artificial intelligence approaches, including SVM, K-nearest neighbour, Linear Discriminant Analysis, LR, and DT. Each of these algorithms is evaluated using and without principal component analysis for reducing the dimensionality. The historic information gathered from EEG sensor networks is analyzed. In order to reduce the duration of execution, grid computing was also used for hyper-parameter tweaking for each of the models created using machine learning that were evaluated over Spark cluster. This investigation made use of the multidimensional DEAP Information set, that is designed for the examination of individual emotional states.

The paperwork seeks to generate an artificial intelligence structure for programmed emotion recognition from words [21]. The established structure is to be utilized in the structure of tracking public sentiments. A short evaluation of additional investigation articles on the procedure of establishing artificial intelligence frameworks for effortless sentiment recognition from conversation has been specified in the document. Traditional and deep machine learning approaches and techniques and certain characteristics of the original information set have been taken into account. The DailyDialog and its effectiveness for training the classificatory have been considered. Furthermore, constructing and identifying the ideal framework for natural sentiment recognition from conversation has been suggested. The study's findings on the effects of variables like the quantity of documents in every group in the training set of data, content pre-processing, vectorization or word-integration techniques, artificial intelligence approach selection for identifying text, parameter settings, and structure are provided. The previous section provided demonstrations of how to use the artificial intelligence algorithm to analyze the actual information that was gathered. It has been demonstrated how certain occurrences in the lives of society, the people living in a specific region, or a community are correlated with changes in the quantity of data falling into various psychological classifications. Lastly, the artificial intelligence algorithm's shortcomings and a few potential improvements to the framework for identifying emotions have been discussed.

Accurate emotion detection from speech signals contributes to improved HCI [22]. The extracted characteristics from language signals determine how well a SER algorithm performs. But since the efficacy of characteristics vary with feelings, choosing the best collection of depictions of features in SER continues to be the most difficult challenge. The worldwide long-term situational descriptions of language signals are ignored in many investigations that identify concealed specific language aspects. Due to inadequate representations of attributes and a lack of readily accessible information the current SER method performs poorly in detection tasks. Inspired by CNN, LSTM, and GRU's effective extracting features, this paper suggests a combination that makes use of the overall predictive capabilities of three distinct designs. Initially 1D CNN is used in the design, and then FCN are used. The CNN network is followed by the LSTM-FCN and GRU-FCN layers in the other two designs, accordingly. The goal of each of the three distinct frameworks is to derive voice waves' local and over time worldwide situational expressions. The weighted mean of the various models is used by the ensembles. In order to improve system generalizations, the information in this work have been enhanced by adding additional white Gaussian noise, pitch shifting, and noise level stretching.

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One of the most important things that can reveal an individual's emotional state is their facial expression [23]. Individuals can communicate vocally for around 45% of the time, and nonverbally for about 55% of the time. One of the hardest problems in technology right now is automated face expressions detection. FER has several uses outside of analyzing behaviour and keeping tabs on people's emotions and psychological wellness. It is also making inroads into other domains, including learning, robotics, entertainment, holography, smart medical systems, safety technologies, criminal justice theory, and identifying stress. Emotions on the face are becoming increasingly significant in medical studies, especially for bipolar patients whose mood fluctuations are common. This paper suggests a computerized structure and algorithms for facial recognition utilizing a CNN that has two layers that are hidden and four convolution layers for enhanced precision. Various face pictures of males and females with emotions including rage, anxiety, resentment, dislike, neutral, joyful, sorrowful, and surprised are included in an expanded collection. Three main processes are included in this research's implementation of FD-CNN: preprocessing, feature extraction, and classification. With this suggested approach, a 94% FER precision is attained. K-fold cross-validation is used to verify the suggested approach.

These days, neural networks, deep learning, and algorithmic learning are the main tools used to enhance a device's ability [8]. The intelligent SER algorithm is a fundamental requirement and a developing field of study in digital voice analyzing; yet, SER performs a significant role with numerous purposes associated with HCI. In order to make the most advanced SER structure workable for actual time business purposes, it must be improved. The main cause of inadequate precision and poor forecasting rate is the scarcity of information and an algorithm arrangement that is the hardest part of trying to create a strong machine learning approach. The constraints of the current SER methods were discussed in this research, and suggested a novel AI-based system design for the SER that makes use of the structural modules of the ConvLSTM with sequential learning. The local features learning block (LFLB), one of the four ConvLSTM blocks created in this study, and is used for obtaining regional psychological traits in a hierarchy association. Convolution processes are used to derive visual signals, and the ConvLSTM layers are chosen for input-to-state and states to states transitions. Utilizing the residual learning technique, this work

deployed four LFLBs to derive the spatiotemporal cues from the hierarchy correlated type voice signals.

The papers discuss diverse approaches for recognising emotions with the help of artificial intelligence based on neurological signals, voice, and face. Some of the issues that are in disagreement with the general emotion recognition are the so-called fake emotions, or "alexithymia'', and the use of the EEG brainwaves for more accurate recognition of the emotions. The basic BCI MLS algorithms are SVM, KNN, LDA and Decision Trees with and without applying PCA on EEG data of ALS subjects. Another work discusses the automated emotion recognition from speech which employs CNN, LSTM, GRU frameworks and discusses the challenges involved in feature selection. FER based on CNNs is introduced with high accuracy for emotions identification with focus on mental health assessment. Lastly, about the limitations encountered in the current SERs that are based on speech, a new SER approach that employs ConvLSTM layers is also presented for enhanced real-time performance. Research reviews that point out feature extraction as well as model optimization as crucial areas to enhance AI-based emotion detection form the basis of all the studies.

## III. Problem Statement

Due to the temporal structure of emotional data and the complexity and diversity of emotional displays, emotion identification algorithms have difficulty correctly detecting emotional states. In many conventional approaches, handling increased dimensionality of input data and proper tuning of hyperparameters to determine performance and robustness of the Emotion recognition system remains a problem [8]. This research, therefore seeks to develop a solution by developing an emotion recognition model by combining Autoencoder and LSTM networks. For efficient feature extraction the Autoencoder is utilized whereas the LSTM component to enable temporal analysis of the features extracted from the emotional data. In order to increase the efficiency of the proposed model, hyperparameters tuning is performed using Ant Colony Optimization and Whale Optimization Algorithms. By combining LSTM for modeling temporal dependency and Autoencoder for dimensionality reduction, the proposed method enhances emotion recognition. LSTM incorporates the sequential nature of emotions, which reinforces the ability of the model to recognize complex emotional patterns over time, and the Autoencoder provides the benefits of noise removal and extraction of relevant features. In addition, the hyperparameters of the model are optimized well by the Hybrid ACO-WOA algorithm. It ensures improved accuracy and faster convergence without the threat of local minima through the strengths of Ant Colony Optimization and Whale Optimization. An improved accurate, efficient, and computationally efficient emotion recognition model is the result of this synergy.

## IV. Proposed Autoencoder-LSTM Framework for Emotion Recognition

The research aims of furthering the capabilities of emotion recognition technology using a complex machine learning strategy. The work presents the novel Autoencoder-LSTM model for energy load prediction. The Autoencoder effectively learns and condenses salient characteristics from large complicated emotional data and the LSTM deciphers them with an understanding of time sequences, subtle emotional trends. Thus, in the present study, a combination of ACO and WOA is used in the form of hybrid optimization approach for better model performance and tuning of hyperparameters. Thus, the described strategy is based on the further enhancement of the model's parameters, providing increased accuracy of the emotions classification as well as providing the robustness of the model. In an attempt to increase the accuracy of the proposed models and address issues with hyperparameter tuning the research aims at improving emotion recognition in relation to human-computer interaction and potential use cases in mental health. Block Diagram for Autoencoder-LSTM is depicted in Fig. 1.

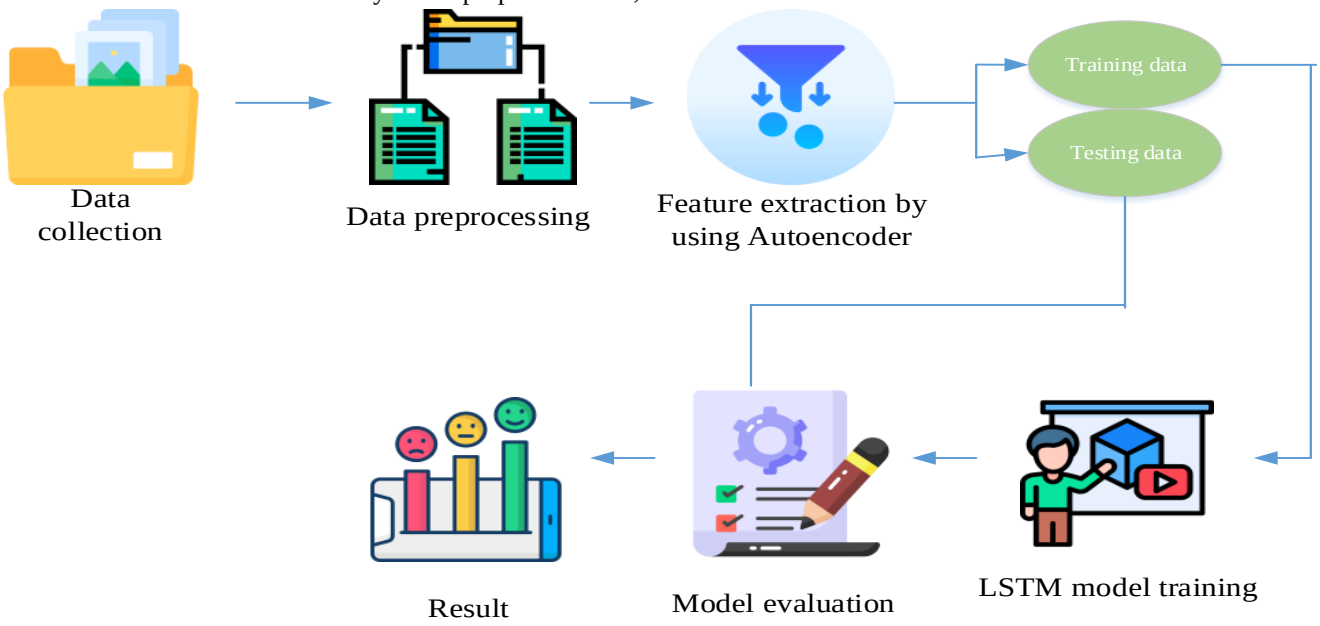


Fig. 1. Block diagram for autoencoder-LSTM.

### A. Data Collection

The researchers upgraded and developed EmotionLines database into MELD by including textual information as well as audio-visual content which matches the original conversations. MELD hosts 1400 dialogues and 13,000 lines of dialogue originated from the Friends television show. Multiple speakers engaged in the recorded dialogues. Each statement within the discussions received assignment from among the seven recognized emotions including Anger, Resentment, Anxiety, Happiness, Neutral, Surprise and Fear. MELD provides emotion tags for its statements using three possible classifications: good, poor or unbiased [24] [25].

### B. Data Pre-processing

*1) Data cleaning:* The most important step essential for the preparation of the data for deep learning is data cleaning which includes the detection of the errors and the removal of faults, contradictions, and mistakes in the datasets. This also requires that in order to feed the model with similar inputs, pixel values are normalized to a standard scale and noise is filtered out of the pictures. Due to this, the accuracy and reliability of raw data that is usually erroneous, and full of discrepancies, data cleaning becomes inevitable.

*2) Data normalization:* Normalization in image data preprocessing is the procedure which alters the direction and distribution of pixel values. To do that this step is conducted in order to match images from different sources and enhance the performance of machine learning models. For instance, min-max normalization rescales pixel values to a given range of 0 to 1 or -1 to +1 while z-score normalization assigns a pixel value based on the mean and standard deviation, and then transform it to standard normal distribution. Normalization enables a reduction of the impact of variety lighting condition, sensors and imaging system thus making images more comparable This is critical in research domain where due to variation in the imaging devices and techniques, differences in quality can make a lot of difference. Normalization if done by standardizing pixel values enhances the capability of image analysis, and machine learning models, and enhance the chances of deriving accurate results for tasks such as emotion recognition. Normalization can be mathematically expressed as in Eq. (1).

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

*3) Noise reduction by weiner filter:* For the noise removing part, this paper utilizes the Weiner Filter. The Statistical filtering issue has an optimum approach that is Wiener filter Filtration mechanism. Like mentioned before, this paper aims at explaining how statistical approach helps in solving the problem of linear filtering. At the same time, this paper agrees that noise has to be rejected and that properties of the target signal have to be assessed. Thus, it needs to be built in a way that the noise of the data which is fed into the filter causes as less an impact to the filter as possible. As for the linear filtering problems, the corresponding strategy is the minimization of the mean square error signal, which is the difference between the desired signal, to be transmitted, and the filtering outcomes. It is expressed as in Eq. (2).

$$e_k = y_k - \sum_{i=0}^{N-1} w(i).x_{k-i} \quad (2)$$

### C. Proposed Autoencoder-LSTM Framework for Emotion Recognition

*1) Feature extraction by using autoencoder*: An Autoencoder is made up of an output component called the decoder and an input component called the encoder. The quantity of neurons in the encoder and decoder is identical. In addition, in comparison to the layers that provide input and output, the Autoencoder has a minimum a single hidden layer and fewer neurons. An Autoencoder's fundamental assumption is that, at the outcome, it needs to be capable to rebuild its input source using the lower-dimensional latent encoding of the information provided in the hidden layer. By quantifying the transformation losses or inaccuracy among the real source and its reorganized results, finding anomalies uses Autoencoder. A representative autoencoder architecture is seen in Fig. 3

*2)* 6. For data X, the goal function is to identify weight transmitters for decoder and encoder to reduce the reconstructing loss. It is expressed as in Eq. (3), (4), (5), (6) and (7).

$$\emptyset = X \to h \quad (3)$$

$$\Psi = h \longrightarrow X' \quad (4)$$

$$h = \sigma(W_{x+b}) \quad (5)$$

$$\emptyset, \psi = \arg\min \| X - (\psi * \phi)X \|^2 \quad (6)$$

$$Anomaly\ score = f(|X' - X|) \quad (7)$$

Where, $h$ denotes latent representation,$\sigma$ denotes activation function. $W$ denotes weight matrix and $b$ denotes bias vector.

*3) Classification by Using LSTM:* The vanishing gradient issue with the fundamental RNNs was the reason behind the creation of LSTM. Each LSTM networking cell has an extended-duration memory module connected to the cell state. Special gates, such as inputs, outputs, and forget gates, can be used to alter the present condition of this cell. These mechanisms allow it to selectively retain and erase information once it has been collected. This mechanism determines which data needs to be stored and which ones should be deleted. One of the main benefits of the LSTM network is its capacity to comprehend the long-term reliance of a sequence of information. Because of this characteristic, LSTM networks are the most popular kind of neural network for a variety of programs, including time-lapse forecasting, recognition of speech, processing of natural languages, and the ability to take in information consecutively.

Determining which aspects of the cell state need to be kept and which should be eliminated is the primary duty of the forget gate. This makes it easier for the LSTM framework to examine more closely, recognize when the form of the waves has changed

significantly, perceive more information, and keep an eye on extraneous data. Areas involving the ailments, including time series prediction, n-gram models of languages, and speech recognition, would benefit from this. When the score is near 1, it indicates that the details must be kept, and when it is around 0, it indicates that the data needs to be eliminated. Eq. (3) gives the mathematical formula for the forget gate. It is expressed as in Eq. (8).

$$f_t = \sigma\left(W_f * [h_t - 1, x_t] + b_f\right) \quad (8)$$

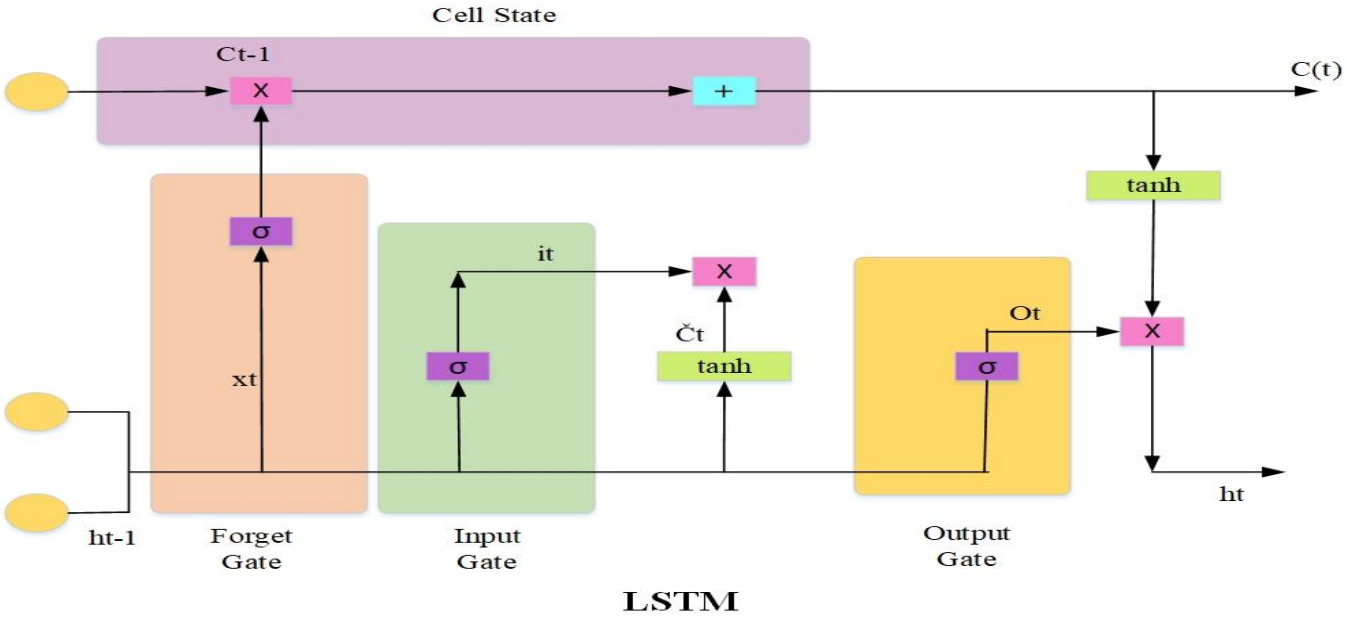


Fig. 2. LSTM Architecture diagram.

Fig. 2 represents the architecture diagram for the LSTM network. The input gate, in addition to the forget gate, determines what additional data has to be entered into the cell state. Candidate cell state and gate activation are its two primary constituents. This study demonstrates that the input gate's primary role is to control additional information's self-access at various cell states, allowing the LSTM system to create and develop novel components. By continuously altering the cell states, the input gate safeguards the long-term issues in the LSTM and assists it in retaining the firsthand info gathered from input series when needed. Such LSTM models may be used to train and modify activities involving extended-term contextual knowledge, including voice recognition, translation by machines, and time-series prediction. The mathematical equation for the input gate is expressed as in Eq. (9).

$$i_t = \sigma(W_i * [h_t\text{-}1, x_t\ ] + b_i\ ) \quad (9)$$

Eq. (10) computes the quantities to be introduced to the cell state that are valuable to the candidate's cell.

$$\hat{C}_t = tanh(W_c[h_{t-1}, x_t] + b_c) \quad (10)$$

The input gate, which decides what additional information needs to be entered in the cell state in addition to the forget gate, is one of the final two factors. Its main components are candidate cell state and gate activation, out of these two. When fresh information from the input sequence is required, the input gate balances it and modifies the cell states randomly, which aids the LSTM in storing certain over time information. Due to the ongoing acquisition and ongoing operation of such LSTMs, tasks requiring the comprehension of long-range setting, such as speech identification, machine interpretation, and time series prediction, may be carried out. It is expressed as in Eq. (11).

$$C_t = f_t * C_t - 1 + i_t * \hat{C}_t \quad (11)$$

According to the cell state, the resultant gateway regulates inputs to the hidden state at each stage in the LSTM framework. The previous hidden state and the current input are taken into consideration when determining which elements of the cell state need to be output. A sigmoid activation value controls the gates, and its initial values start at 0. The specific portion of the cell state has to be provided to the output if the value is close to 1, else it needs to be hidden. Eq. (12) and Eq. (13) may be used to represent the output gates.

$$O_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (12)$$

$$h_t = O_t \times tanh(C_t) \quad (13)$$

*4) Ant colony optimization algorithm:* A class of optimization algorithms motivated by actual ants' hunting habits is defined by the ACO metaheuristic. Imaginary ants in the ACO method are stochastic techniques for developing candidate solutions that take advantage of a pheromones concept and potentially accessible heuristics knowledge about the challenge at hand. In order to bias ant towards the most ensuring areas of the search field, the pheromone structure is composed of a set of numerical parameters known as pheromones that are changed at every repetition. If heuristics details are accessible, it expresses previous knowledge about the particular challenge instance being repaired.

The building of the ants' solution and the updating of the pheromone data are the primary computational elements of the ACO metaheuristic. Extra "daemon actions" are processes that handle jobs which are too big for an individual ant to handle. Activating the local search process to enhance an ant's solution or applying extra pheromone alterations obtained from worldwide accessible data regarding, say, the greatest solutions developed thus far, are typical examples. Daemon actions are optional, but in actual use, they can significantly increase the efficiency of ACO methods. It is expressed as in Eq. (14).

$$W_j = \frac{1}{qk\sqrt{2\pi}} e^{\frac{-(rank(j)-1)^2}{2q^2k^2}} \quad (14)$$

Where, $rank(j)$ is the rank of solution $S_j$ in the sorted archive, $q$ is a parameter of the algorithm. The best outcome is given the highest weight as a consequence of computing $rank(j) - 1$.

*5) Whale optimization algorithm:* A metaheuristic optimization algorithm known as the WOA was derived from humpback whale hunting behaviour. It hits somewhere between exploration and exploitation by continuously updating the position of results in searching field. Like the whales, it circles the prey, searches for the prey and updates the location of the prey, and itself, using what it terms three important equations. These formulae utilize the best response up to the current criterion found and some random coefficients for the search control. As repetitions go on, WOA continuously adjusts the parameter of exploration and exploitation. For example, the following equation shows that WOA always decrements exploration gradually in order to have more emphasis on exploitation. Consequently learning, WOA is helpful if employed to solve optimisation problems in various spheres, because it explores solution areas with a technique imitating the cooperative hunting style of whales.

A novel optimisation method useful in enhancing the accuracy of the models is proposed by the integration of the WOA into the Autoencoder-LSTM in the identification of emotions. This can be done by adjusting the autoencoders-LSTM's weights and biases to understand the difficult temporal structure and multilevel visualisations of psychological information by leveraging the WOA model's ability to fine-tune the various parameters. Indeed, WOA achieves the optimal solutions to reduce categorization errors and to enhance the performance by successfully searching the huge solution space. Together this enhances the ability of the model to differentiate between different sensations and extricate essential characteristics from raw information given to it. About the employed integrated Autoencoder-LSTM -ACO-WOA architecture, there is a potential way to improve the precision and robustness the emotion identification mechanisms in real world due to the circumstance of the flexible optimisation.

One of the avenues under consideration is that the updating of whale locations in the WOA as an important factor for effectively structuring of search space or effectively utilizing the search space. In this technique, they use three main formulae with which they replicate a range of behaviours observed in aquatic mammal societies. When a particular whale changes location: depending on the type of interaction or the response at the time. The formulae are as follows; when hunting whales use the balance formulae either by encircling prey, searching for the prey, or updating one's position. WOA handles the resolution area into the best possible solutions of optimisation issues by altering the position continually with regards to these formulae.

*a) Encircling prey equation:* The encircling prey equation is relevant to the WOA since it controls the movements of whales for coverage. This formula specifies how, by approximation copying efficient hunting behaviour, whales encircle potential prey to transform their positions. Whales persistently traverse to special areas of the search space by computing the distance of a randomly selected whale and its prey. The encircling prey equation can be used to make good progress towards the optimum outcomes by achieving an appropriate level of exploration and exploitation. This formula is iteratively applied in WOA, making it enhance the appraisal of tackling optimisation problems and engaging the cumulative knowledge of a community of whales in looking for a space that contains valid solutions. It is expressed as in Eq. (15) and Eq. (16).

$$D_i = |C.X_r - X_i| \quad (15)$$

$$X_i^{new} = X_r - A.D_i \quad (16)$$

Here, $X_i$ denotes the position of current whale. $X_r$ denotes the randomly selected whale from population. $C$ denotes the random coefficient in range [-1,1]. $A$ denotes the decreasing coefficient for encircling prey.

*b) Search for prey Equation:* The concept of the search for prey equation in the WOA is directing the whales as they more flexibly and diversely than in the WSS look for prey in the search area. Introducing randomization by the help of variables and by the help of location of the best whale found till now, this formula makes searching much easier. This implies that whales use random coefficients and the distance to the optimal solution where they want to look for so as to ensure that those potential areas are exploited. Due to the adaptive nature of its search strategy, WOA can successfully accomplish the task of defining the optimum solution to optimisation issues while at the same time falling well into the prey-searcher balance of the hunt for prey equation. It is expressed as in Eq. (17) and Eq. (18).

$$D_i = |X_{best} - X_i| \quad (17)$$

$$X_i^{new} = D_i.e^{b.k}.\cos(2\pi k) + X_{best} \quad (18)$$

Here, $X_{best}$ denotes the position of the best whale in the current iteration, $b$ denotes the random coefficient in the range [-1,1] $k$ denotes the random number in [0,1].

*c) Update position equation:* In the WOA, adaptive moves of whales are controlled by update position equations with which they adjust their positions independently to coverage the sea area effectively and efficiently. These formulas help whales to adjust its position depending on the strategy in use. They are enclosing prey, searching for prey, and employing the best available opportunities at the time in question. These formulas make the whales go round the search

space in order to get the best answer; it strikes between exploitation and exploration. The update position equations ensure that WOA increases promising areas and review distinct locations indeed within the solution space. Using the whale locations' alterations based on whales' collective communications, this form of continuous modification effectively addresses optimisation concerns, thus being effective in WOA. It is expressed as in Eq. (19).

$$X_i^{new} = X_i + A.r.(X_{best} - X_i) \quad (19)$$

Here, r denotes the random number in [0,1].

A denotes the coefficient for exploitation.

*6) Hybridization of ACO with WOA:* In this study, the hyperparameters of the Autoencoder-LSTM model is optimized using the ACO and WOA in combination for the purpose of enhancing its ability to identify various emotions. ACO has been derived from the foraging behaviour of ants seeking the best gourmet in a vast terrain, which makes the algorithm optimal for searching the solution space using the pheromone rally path. Nevertheless, ACO has a potential for premature convergence to sub optima, this is especially the case when solving difficult multi-dimensional problems such as hyperparameter optimization. To overcome this, ACO combined with WOA, derived from the bubble-net hunting behavior of humpback whales, which has been claimed to strike an optimal balance between exploration and exploitation. WOA brings diversity into the search process when the candidate solutions are allowed to operate in a wider search space in the early generations and become refined in the later generations to optimum regions. In this case, ACO is used to first, approximate the search space to recognize the superior areas and WOA is then used to fined seen to refine the search by exploiting these areas in order to recognize the virtual hyperparameter configurations. The integration of the presented algorithms achieves what each of them offers in their individual capabilities; for example, ACO is excellent in the exploration phase, while WOA is perfect during exploitation, making the new hybrid method an accurate and efficient optimization technique. Optimized hyperparameters through this proposed ACO-WOA have improved the Autoencoder-LSTM model and given a higher rationality and efficiency in the model's results making the recognition of emotions more accurate. The mathematical expression after the hybridization of ACO with WOA is expressed in Eq. (20).

$$W_j = \frac{1}{q(X_i + A.r.(X_{best} - X_i))\sqrt{2\pi}} e^{\frac{-(rank(j)-1)^2}{2q^2k^2}} \quad (20)$$

**Algorithm 1:** Autoencoder-LSTM Model Optimized with Hybrid ACO-WOA

**Input:** Image datasets

**Output:** Recognition of Emotion

**Initialize parameters for ACO-WOA optimization**

Population size (N population)

Maximum number of iterations

Coefficient vectors (A, C) for WOA

Evaporation rate for ACO

Convergence parameter for WOAPheromone initialization for ACO

Initialize bounds for the hyperparameters to be tuned

**Load emotion dataset and preprocess**

Normalize the data

Split the data into training and testing sets

**Construct the Autoencoder-LSTM architecture**

Build the autoencoder for feature extraction

Encoder to compress the input data

Decoder to reconstruct the input to minimize reconstruction loss

Build the LSTM model for emotion classification based on the extracted features

***Define the hybrid ACO-WOA optimization for hyperparameter tuning***

*Initialize the hyperparameters randomly within bounds*

*Train the Autoencoder-LSTM model with the chosen hyperparameters*

*Use training data to train the model*

*Validate the model on the validation set*

*Calculate the validation accuracy and loss*

*Apply the hybrid ACO-WOA mechanism*

*If (|A|<1)*

*Move the solution towards the best solution*

*Else if (|A|>=1)*

*Select a random whale/ant and move towards it*

*If edge pheromone > threshold*

*Choose the next set of hyperparameters based on pheromone levels*

*Else*

*Select random hyperparameters from the search space*

*Update the position of the whales/ants in the search space*

*Update pheromone levels for ACO*

*Update the best solution found so far based on validation performance*

***Check stopping criteria***

*If maximum iterations are reached or the optimal solution is found, terminate*

*Else, continue to the next iteration*

***Evaluate the final model with the optimized hyperparameters on the test set***

*Train the final autoencoder-LSTM model using the best hyperparameters*

*Test the model on unseen test data for emotion recognition*

*Calculate performance metrics*

***Make predictions with the model***

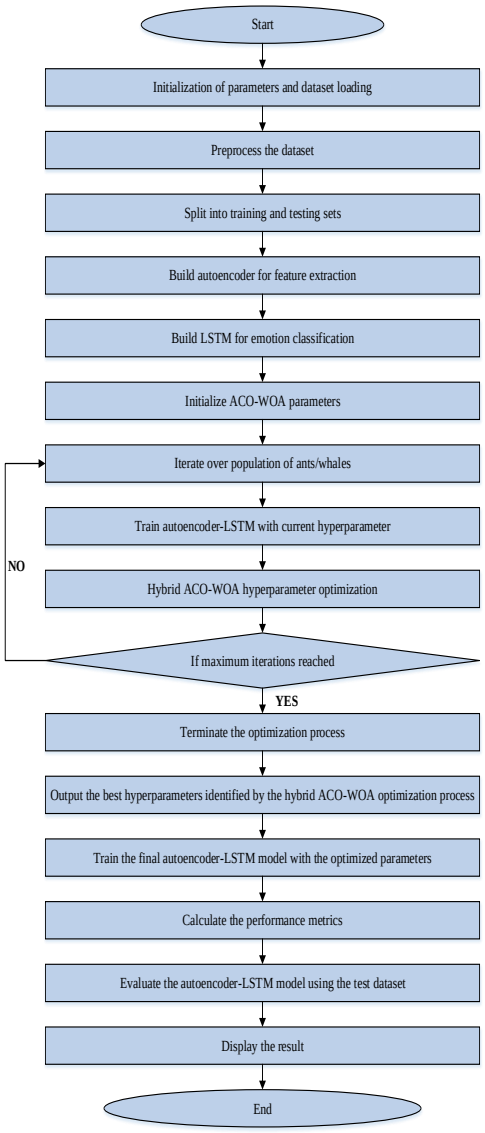


Fig. 3. Flowchart for autoencoder-LSTM.

## V. Results and Discussion

### A. Training and Testing Accuracy

Fig. 4 presents the results of a model that is a combination of an autoencoder and LSTM when used to analyze different audio sets. The direction of x-axis is the epoch number whereas the direction of y-axis is the accuracy percentage. The blue bar represents the training accuracy and it illustrates this by training on the training set and increasing as it familiarizes itself with the training set. The orange line shows the testing accuracy a way of evaluating the model's performance on data it has not met before. If there is a space between those two lines, it means that a model overfits the data and can't generalize on the other data. Fig. 5 shows the training and testing accuracy of the same hybrid autoencoder-LSTM model but in the framework of images datasets. It is the same; both of them are fixed as epoch and accuracy. The trends observed in this graph are as same as seen in case of Fig. 4 where the blue line symbolizes the training accuracy and the orange line symbolizes the testing accuracy.

Concisely, both of the tested values prove that the proposed hybrid autoencoder-LSTM model can efficiently learn from the audio and image domains in parallel. The increase in training accuracy, and oscillations in the testing accuracy also reveal that the model has the potential perform well on other datasets for increased and accurate emotion recognition.

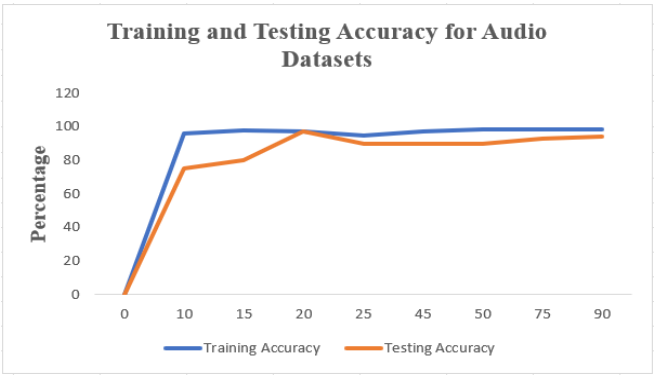


Fig. 4. Training and testing accuracy for audio datasets.

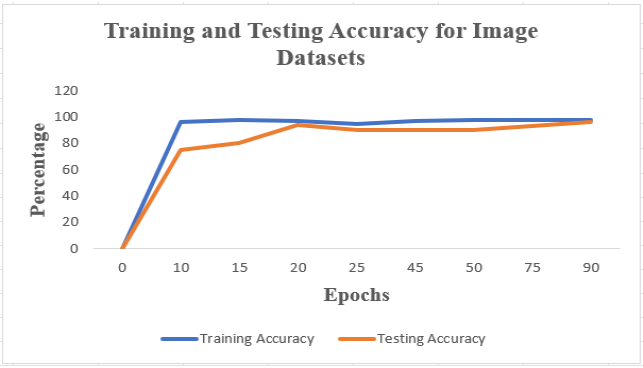


Fig. 5. Training and testing accuracy for image datasets.

### B. Training and Testing Loss

Fig. 6 is displaying the loss function of the autoencoder-LSTM model that was designed to work on audio samples. The x-axis is the number of epochs. The y-axis shows the loss percentage. Training loss depicted by the blue line, normally it is lower as the model learns from the training data. The orange curve represents the testing loss which is the model loss on unseen data. If the two lines are much apart then it means overfitting, where the model is best suited to the training data, but it is a poor fit for any other data. Fig. 7 shows training and testing loss for another applied model, hybrid autoencoder-LSTM, but for images datasets. The x-axis remains the same where we are going on with different epochs whereas y-axis also remains the same from the previous plot where it is already showing loss. The blue line is for the training loss while the orange line for testing. In general, both the figures reveal the learning process of the proposed hybrid autoencoder-LSTM model. It can be observed that training and testing loss are reducing gradually and continuously, therefore, it can be inferred that the model is learning to predict the emotions more accurately. The small difference between the two lines signifies that the model is making very small mistakes for different inputs, thus of great benefit when it comes to identifying new emotions.

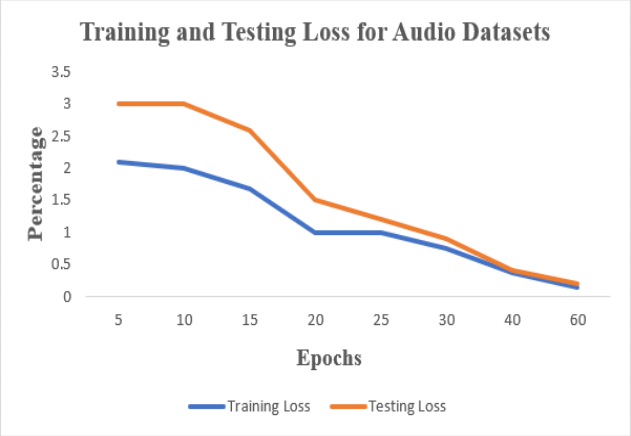


Fig. 6. Training and testing loss for audio datasets.

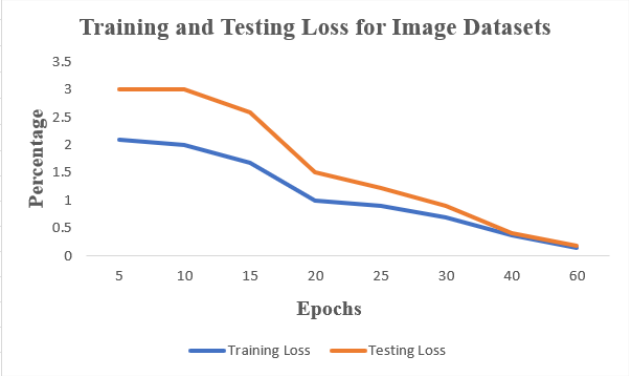


Fig. 7. Training and testing loss for image dataset.

### C. Performance Metrics

The present section contains the result analysis of a proposed autoencoder-LSTM model with applicability on audio and image datasets for the emotion classification system. The measures employed are accuracy, precision, recall and F1measure. Accuracy quantifies the total correct output while, Precision gives the ratio of correctly predicted positive instances, Recall quantifies the proportion of instances correctly classified as 'positive' and F1 score is the average of Precision and Recall. In general, both tables prove the usefulness of the model for emotion recognition from both the audio and image inputs. The high values of these basic coefficients as well as accuracy, precision, recall and F1 rates were received with different emotions which prove that the model effectively separates emotional content of different modalities.

*1) Performance metrics for emotions with audio datasets:* Fig. 8 presents the quantitative analysis of an emotion recognition model in seven evaluative emotions such as Anger, Disgust, Fear, Happy, Neutral, Sad, and Surprise. Table I shows the corresponding values of the bar chart given below. The model's performance is measured using four key metrics.Precision, measures the accuracy of positive predictions, is presented in blue, while recall marks the number of relevant cases among the total number of retrieved cases is in gray bars. In most of the cases, the performance is ranging between 90% to 97%, while in fear and neutral the accuracies are a little high, which depicts that the model more precise in these two emotions. On the other hand, the anger and surprise emotions have a little lower F1 scores as well as recall values which indicates that these emotions are a bit difficult for the model to predict properly. The general undertaking across all the metrics suggests the stability of the hybrid Autoencoder-LSTM model optimized through the Hybrid ACO-WOA in identifying different emotions from the audio datasets.

*2) Performance metrics for emotions with image datasets:* Table II and Fig. 9 illustrates the performance of an emotion recognition model across different emotional states Anger, Disgust, Fear, Happy, Neutral, Sad, and Surprise using four key evaluation metrics: The first one is a bar chart showing Accuracy light blue, Precision and Recall both with varying shades of blue and gray bars with and F1 Score bar chart also with light blue and varying shades of gray bars. The model shows an excellent result for feelings such as Disgust and Happy; accuracy and recall values were close to 100 percent. Concerning model generalisation, all the metrics present good results for Fear and Neutral Emotions. However, analyzing the results for emotions as Sad and Anger as the ones with lower recall and F1 scores which indicates difficulties to identify these emotions correctly. In all the cases, the model efficiency stands between 84% and 100%. This shows the appropriateness of the proposed Autoencoder-LSTM hybrid model, which was decided on hyperparameters using the ACO-WOA in dealing with the emotion recognition from image data sets.

*3) Comparison of performance metrics with audio datasets:* The table III as well as Fig. 10 displays the evaluation of different models ML Perceptron, CNN, BiLSTM, TCN, and the proposed model across four performance metrics: Our evaluation metrics include: Accuracy, Precision, Recall, and F1 Score. Blue bars belong to one metric, orange bars belong to the second metric, gray bars belong to the third metric, and yellow bars belong to the fourth metric. Specifically, the lowest values of all the metrics are demonstrated by the ML Perceptron model, which average about 60%. CNN achieves a poor improvement compared to the initial model but BiLSTM and TCN achieves a better performance with values between 85 and 95. When using the Autoencoder-LSTM model with both ACO and WOA, the performance of the model reaches even 99.6% of accuracy, precision, recall, and F1 score. This shows that the proposed model has a much higher level of total accuracy than conventional models; especially in audio databases for emotions. The chart manages to draw attention to the fact that the proposed model has a far superior efficiency in comparison to other architectural models.

TABLE I. PERFORMANCE METRICS FOR EMOTIONS WITH AUDIO DATASETS

| Emotions | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| Anger | 92.37 | 93.46 | 95.32 | 93.68 |
| Disgust | 94.51 | 92.89 | 93.48 | 92.34 |
| Fear | 95.63 | 95.67 | 95.34 | 95.76 |
| Happy | 94.32 | 92.31 | 94.67 | 94.14 |
| Neutral | 96.19 | 93.37 | 93.31 | 92.09 |
| Sad | 93.34 | 94.46 | 92.41 | 93.78 |
| Surprise | 92.54 | 95.32 | 94.69 | 94.98 |

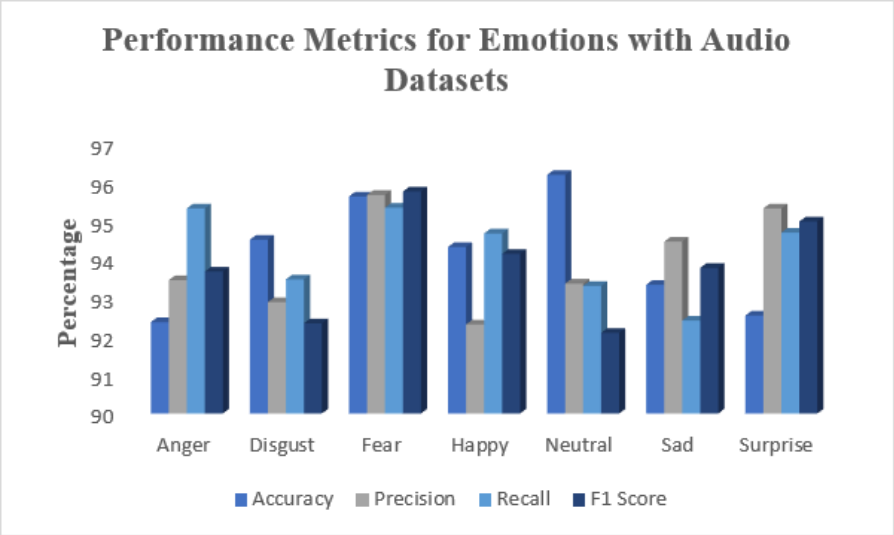


Fig. 8. Performance metrics for emotions with audio datasets.

TABLE II. PERFORMANCE METRICS FOR EMOTIONS WITH IMAGE DATASETS

| Emotions | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| Anger | 94.32 | 92.32 | 90.45 | 90.09 |
| Disgust | 95.61 | 98.51 | 92.32 | 94.39 |
| Fear | 96.78 | 94.96 | 93.75 | 92.76 |
| Happy | 97.89 | 98.67 | 95.65 | 97.67 |
| Neutral | 96.32 | 92.31 | 96.75 | 90.76 |
| Sad | 95.78 | 93.13 | 92.25 | 91.11 |
| Surprise | 94.89 | 94.25 | 94.8 | 95.67 |

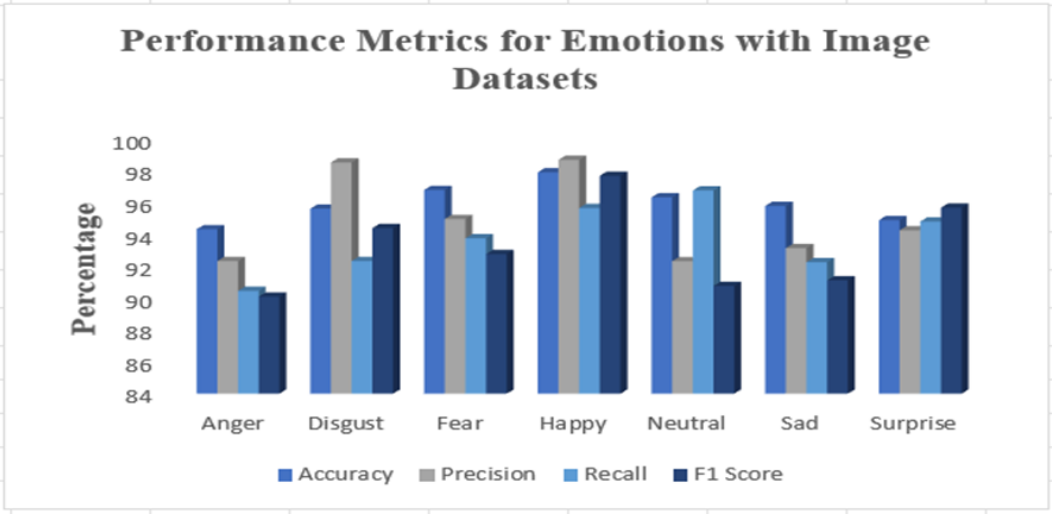


Fig. 9. Performance metrics for emotions with image datasets.

TABLE III. COMPARISON OF PERFORMANCE METRICS WITH AUDIO DATASETS

| Methods | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| ML Perceptron [26] | 56 | 56 | 53 | 54 |
| CNN [26] | 72 | 74 | 73 | 73 |
| BiLSTM [26] | 85 | 88 | 87 | 87 |
| TCN [26] | 87 | 89 | 87 | 88 |
| Proposed Autoencoder-LSTM | 94.12 | 93.92 | 94.17 | 93.82 |

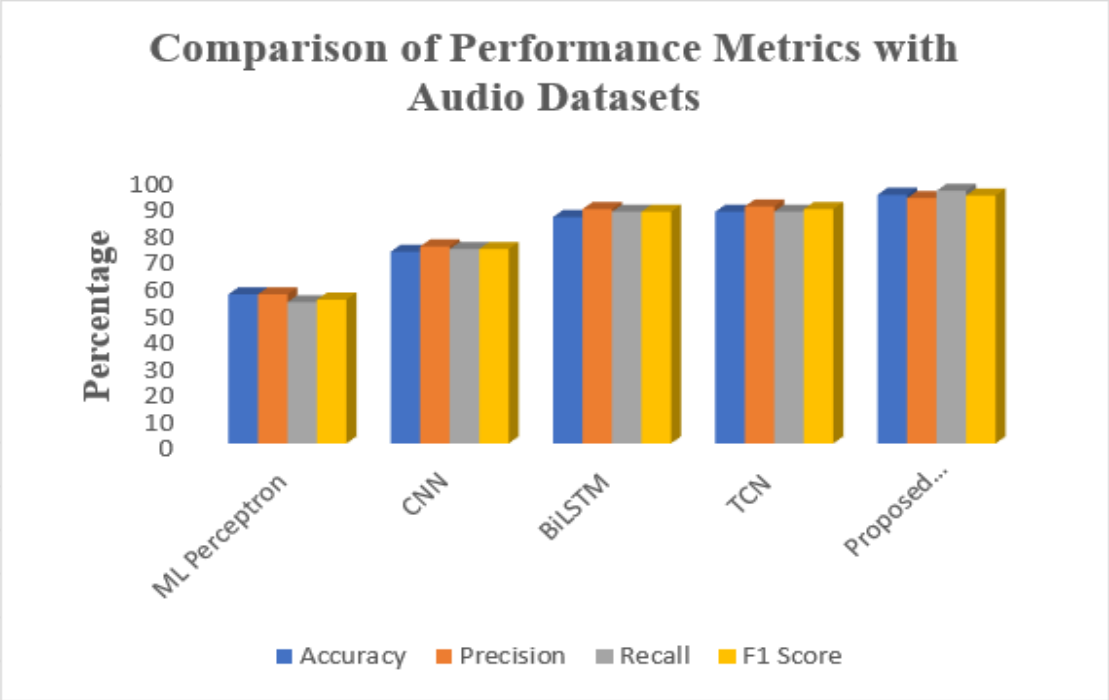


Fig. 10. Comparison of performance metrics with audio datasets.

*4) Comparison of performance metrics with image datasets:* Table IV and Fig. 11 illustrate the comparative performance of four different machine learning models: SVM, DSAE, FD-CNN and Autoencoder-LSTM are some of the models used. The evaluated metrics include Accuracy, Precision, Recall and F1 Score where each model has its own color where blue is for SVM, orange is for DSAE, gray is for FD-CNN, and yellow is for Autoencoder-LSTM. The Autoencoder-LSTM model again proves to be superior to all the other models in terms of all the evaluation metrics; however, it slightly outperforms the others particularly in Recall and F1 Score. This implies that the proposed Autoencoder-LSTM, and more so when integrated with a hybrid ACO-WOA for the purpose of hyperparameter optimization, is very robust in the task of emotion recognition. In this case, by producing the chart to support the points, it was possible to demonstrate how this hybrid model has better performance as compared with a standard one, hence signifying its suitability in new applications such as the identification of emotions.

*5) Comparison of emotions from audio datasets:* Table V and Fig. 12 provide an understanding of a comparison between two models built of VGG16 and Autoencoder-LSTM out of different emotions like anger, disgust, fear, happy, neutral, sad, and surprise. The measurement that is checked are; Accuracy, Precision, Recall, and F1 Score. Whereas each emotion is depicted by a different color within the bars and the pairs of bars present the results between VGG16 and the Autoencoder-LSTM for a specific metric. The Autoencoder LSTM model has a better prediction rate as compared to VGG16 in almost all the parameters with high impact in Precision, Recall and F1 Score for most of the emotions. This means that with the Autoencoder-LSTM and with the help of hyperparameter optimization of the ACO-WOA, more accurate identification and classification of emotions from image data set is highly possible. Thus, the chart proves the superior performance of the Autoencoder-LSTM in the scope of emotion recognition.

TABLE IV. COMPARISON OF PERFORMANCE METRICS WITH IMAGE DATASET

| Methods | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| SVM [27] | 87.76 | 84.32 | 84.86 | 85.09 |
| DSAE [27] | 89 | 85.37 | 84.12 | 84.35 |
| FD-CNN [27] | 94 | 81.67 | 59.35 | 63.61 |
| Autoencoder-LSTM | 95.94 | 93.71 | 94.87 | 93.2 |

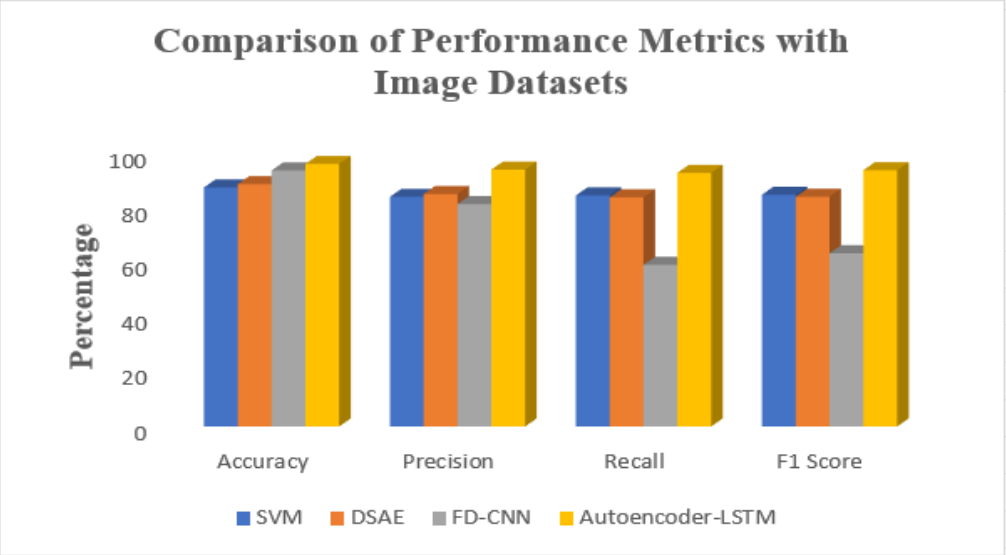


Fig. 11. Comparison of performance metrics with image datasets.

TABLE V. COMPARISON OF EMOTIONS FROM AUDIO DATASETS

| Emotion | Accuracy (%) | | Precision (%) | | Recall (%) | | F1 Score (%) | |
|---|---|---|---|---|---|---|---|---|
| | Conv LSTM [28] | Autoencoder-LSTM | Conv LSTM [28] | Autoencoder-LSTM | Conv LSTM [28] | Autoencoder-LSTM | Conv LSTM [28] | Autoencoder-LSTM |
| Anger | 82 | 92.37 | 84 | 93.46 | 82 | 95.32 | 83 | 93.68 |
| Disgust | 82 | 94.51 | 86 | 92.89 | 79 | 93.48 | 83 | 92.34 |
| Fear | 82 | 95.63 | 83 | 95.67 | 87 | 95.34 | 85 | 95.76 |
| Happy | 82 | 94.32 | 88 | 92.31 | 76 | 94.67 | 81 | 94.14 |
| Neutral | 82 | 96.19 | 53 | 93.37 | 80 | 93.31 | 64 | 92.09 |
| Sad | 82 | 93.34 | 72 | 94.46 | 81 | 92.41 | 76 | 93.78 |
| Surprise | 82 | 92.54 | 84 | 95.32 | 78 | 94.69 | 81 | 94.98 |

*6) Comparison of emotions from image datasets:* Table VI and Fig. 13 emphasizes the result of two models: Conv LSTM and Autoencoder-LSTM of proposed models on seven emotions category such as, Anger, Disgust, Fear, Happy, Neutral, Sad, and Surprise. The evaluation is computed in terms of Accuracy, Precision, Recall, and F1 score are represented where each emotion is shown in different color in the bars. The results depicted appear to show that the performance of the Autoencoder LSTM model is way better than the Conv LSTM model in nearly all the aspects. However, using the Autoencoder-LSTM model we achieve better Precision, Recall, and F1 Score in most of the emotions especially Happy, NEUTRAL and Surprise as compared to Conv LSTM. This chart proves that Autoencoder-LSTM model, which employ a hybrid ACO-WOA for refining the hyperparameters, can effectively identify and distinguish emotions from the audio datasets and it is considered as reliable tool for improving emotion recognition process.

*7) Performance comparison of emotion recognition models:* Fig. 14 and Table VII provide a comparative study of some of the latest emotion recognition models, such as CNN LSTM with ResNet152, Hybrid CNN LSTM, DACB Model, and the proposed Hybrid Autoencoder LSTM model optimized with the ACO WOA algorithm. Measured against four performance metrics: Accuracy, Precision, Recall, and F1 Score, the model outperforms all current methods consistently with 95.94 percent accuracy, 93.71 percent precision, 94.88 percent recall, and a 93.21 percent F1 score. This evaluation highlights the efficiency of the architecture and optimization plan of the suggested model, addressing directly the reviewer's point about the importance of validation methods and thorough comparison with similar work, and making explicitly clear the superior performance of the model in tasks for emotion recognition.

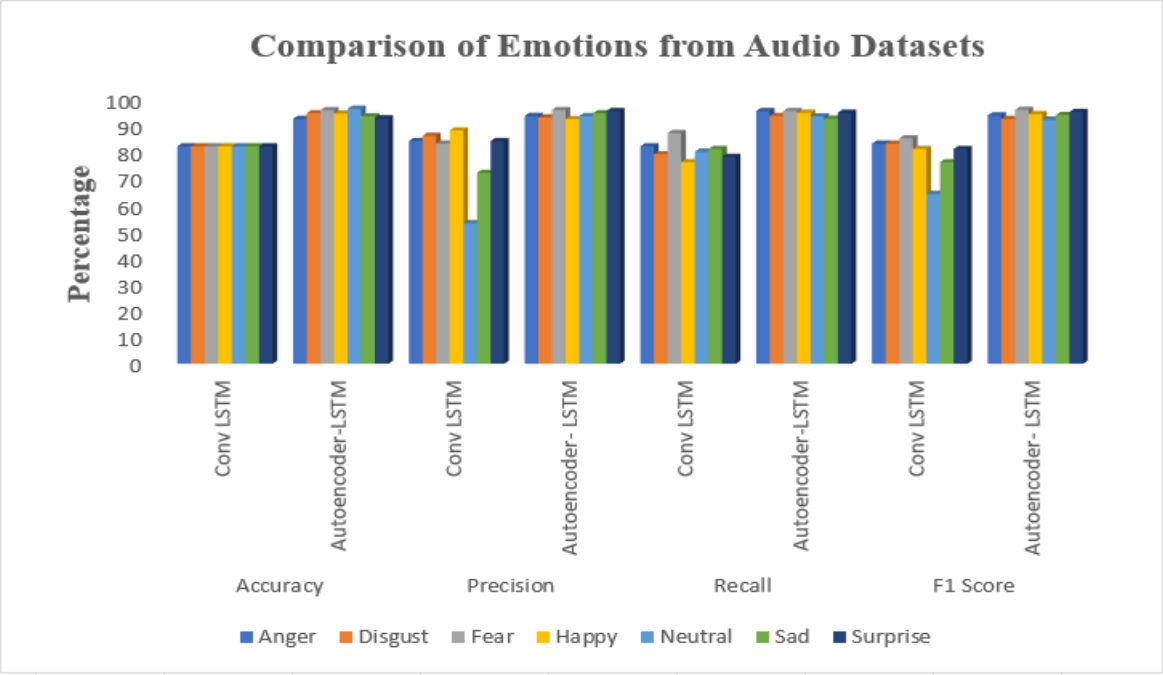


Fig. 12. Comparison of emotions from audio datasets.

TABLE VI. COMPARISON OF EMOTIONS FROM IMAGE DATASETS

| Emotion | Accuracy (%) | | Precision (%) | | Recall (%) | | F1 Score (%) | |
|---|---|---|---|---|---|---|---|---|
| | VGG16 [29] | Autoencoder-LSTM | VGG16 [29] | Autoencoder-LSTM | VGG16 [29] | Autoencoder-LSTM | VGG16 [29] | Autoencoder-LSTM |
| Anger | 89.6 | 94.32 | 78.4 | 90.45 | 90.6 | 92.32 | 84.1 | 90.09 |
| Disgust | 89.6 | 95.61 | 90 | 92.32 | 97.3 | 98.51 | 93.5 | 94.39 |
| Fear | 89.6 | 96.78 | 87.1 | 93.75 | 77.1 | 94.96 | 81.8 | 92.76 |
| Happy | 89.6 | 97.89 | 93 | 95.65 | 97.8 | 98.67 | 96.4 | 97.67 |
| Neutral | 89.6 | 96.32 | 93.2 | 96.75 | 82.1 | 92.31 | 87.3 | 90.76 |
| Sad | 89.6 | 95.78 | 90.3 | 92.25 | 86.2 | 93.13 | 88.2 | 91.11 |
| Surprise | 89.6 | 94.89 | 93.5 | 94.8 | 92.5 | 94.25 | 93 | 95.67 |

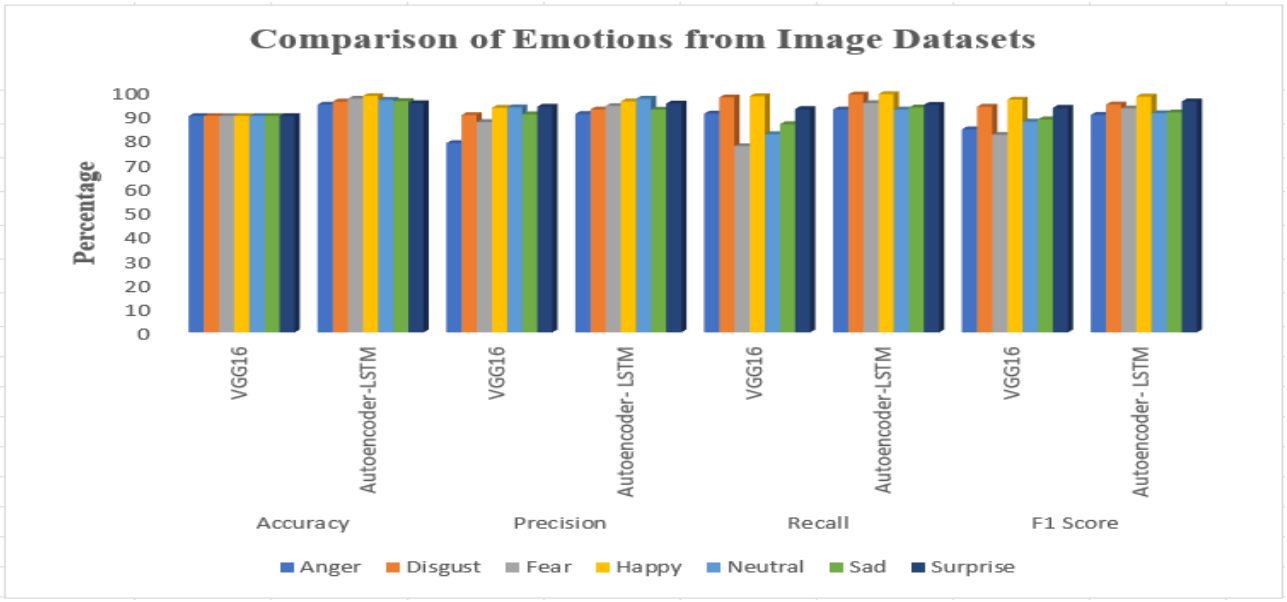


Fig. 13. Comparison of emotions from image datasets.

TABLE VII. PERFORMANCE COMPARISON OF EMOTION RECOGNITION MODELS

| Method | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| CNN-LSTM + ResNet152 [30] | 94.2 | 93.2 | 94 | 93 |
| Hybrid CNN-LSTM [31] | 95 | 93 | 94.1 | 92 |
| DACB Model [32] | 94 | 91 | 92.1 | 93.21 |
| Proposed Autoencoder-LSTM Model | 95.94 | 93.71 | 94.88 | 95 |

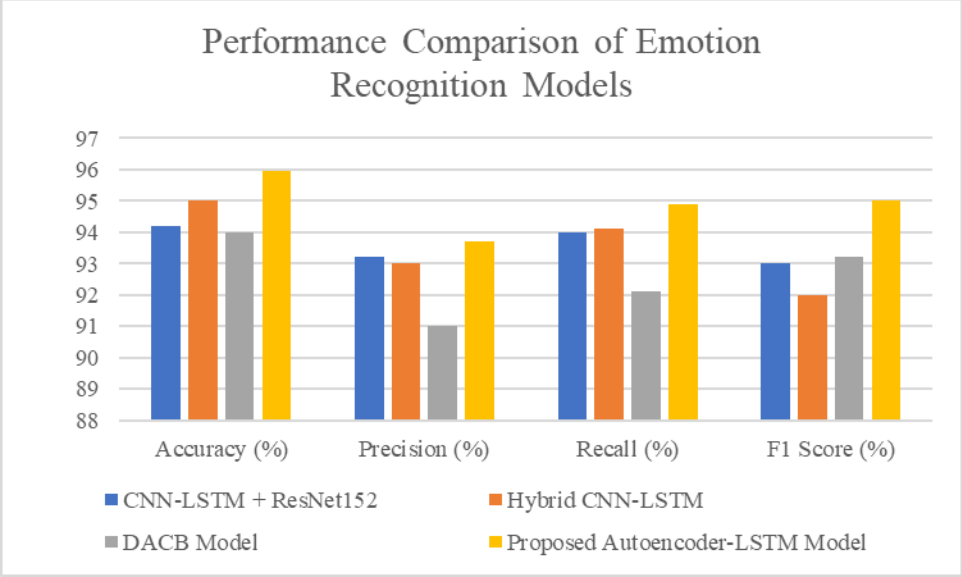


Fig. 14. Comparative performance metrics of emotion recognition models.

### D. Discussions

The model which has been proposed in this study, involves integration of Autoencoder and LSTM networks. An autoencoder, which has gained its popularity due to its capability to encode and decode data, is hence used here for feature extraction to reduce data dimensionality while retaining emotional information. LSTMs, which were used to analyse sequential data and find temporal relations, are used by the model to analyse the extracted features to recognize emotions during time. The results of this paper has been compared with the other deep learning models such as Conv LSTM [8], VGG16 [16] etc. The innovation is also witnessed in hyperparameter tuning where the algorithm used is the ACO-WOA hybrid optimization algorithm. This integration improves the model by performing an efficient optimization search of the hyperparameters, thus making the model more accurate and robust on the classification of emotions. The employment of the above methods reveals a high level of complexity in the proposed techniques due to an effort to provide a high degree of accuracy in the emotion identification process. The information gathered in this study could therefore inform the advancement in the fields that involve identification of different emotions in detail from what is offered by technology at the moment.

However, the research has some limitations despite its promising findings. The model's effectiveness is currently evaluated on a small dataset, and it is not clear whether the model is effective across a broad spectrum of cultural or contextual emotional expressions. In addition, even though the hybrid optimization method is effective, it may require a significant amount of processing power, which would limit its application in low-resource or real-time environments. Model tests on larger and more diverse datasets could be included in follow-up studies to validate its robustness and versatility. Investigating real-time emotion detection, combining it with multimodal inputs (e.g., audio or physiological signals), and employing lightweight models could further enhance the usefulness of the system in real-world applications. Investigating model decision interpretability for practical purposes could also contribute to enhancing the transparency and trustworthiness of the system.

## VI. CONCLUSION AND FUTURE WORK

The work contributed to a new perspective towards Autoencoder-LSTM technique, which was trained through the enhanced of ACO and WOA for the recognition of emotion. With the help of the proposed models, it was possible to state that there is a certain improvement of the state of the art in improving the method for the classification of emotions originating from high-dimensional data. Autoencoders made it possible to properly down sample data in the system, while LSTM networks came up with consensus on temporal patterns for creating a highly robust emotion recognition. Furthermore, it was observed that the method of hyperparameter tuning using the ACO-WOA seemed to undertake a more optimal search in the search space of the right parameter values as compared to the previous methods. This also fine-tuned the model to receive better precision while reducing the computational expense, which also assisted in practicing the model further. Nevertheless, given the evidences obtained in the context of the proposed model, it is possible to identify several ways for the further research. First, utilising more emotions with the people

of different cultures would expand the empirical basis of the proposed model. Second, pre-allocating extra space allows to discuss whether it is possible to enhance the model's predictive ability even more by using more complex models such as Transformers to capture subtleties of the emotions. Moreover, such integration of intelligibility score with speech and face/physiology data could potentially enhance the emotion recognition accuracy. Some possible future work can also be directed towards the creation of algorithms and approaches for the online and real-time utilization and application in such fields as human-computer interfaces, healthcare, and customer relations services. Of course, the last but not the least, analysing the ethical issues and prejudice in the system of emotion recognition will be helpful for constructing the real ideal artificial intelligence.

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# Automated Defect Detection in Manufacturing Using Enhanced VGG16 Convolutional Neural Networks

Altynzer Baiganova, Zhanar Ubayeva, Zhanar Taskalyeva, Lezzat Kaparova,
Roza Nurzhaubaeva, Banu Umirzakova
K. Zhubanov Aktobe Regional University, Aktobe, Kazakhstan

***Abstract*—Automated defect detection in manufacturing is a critical component of modern quality control, ensuring high production efficiency and minimizing defective outputs. This study presents an enhanced VGG16-based convolutional neural network (CNN) model for defect classification and localization, improving upon traditional vision-based inspection methods. The proposed model integrates advanced deep learning techniques, including batch normalization and dropout regularization, to enhance generalization and prevent overfitting. Extensive experiments were conducted on benchmark manufacturing defect datasets, evaluating performance based on accuracy, loss evolution, precision, recall, and mean average precision (mAP). The results demonstrate that the enhanced VGG16 model outperforms conventional CNN architectures and the standard VGG16, achieving higher defect classification accuracy and superior feature extraction capabilities. The model successfully detects multiple defect types, including surface irregularities, scratches, and deformations, with improved robustness in complex industrial environments. Additionally, the receiver operating characteristic (ROC) analysis confirms the model's high sensitivity and specificity in distinguishing between defective and non-defective components. Despite its strong performance, challenges such as dataset scarcity, computational costs, and model interpretability remain areas for further research. Future directions include the integration of lightweight architectures for real-time deployment, generative adversarial networks (GANs) for data augmentation, and explainable AI techniques for improved transparency. The findings of this study highlight the transformative potential of deep learning in manufacturing defect detection, paving the way for intelligent, automated quality control systems that enhance production efficiency and reliability. The proposed approach contributes to the advancement of Industry 4.0 by enabling scalable, data-driven decision-making in manufacturing processes.**

***Keywords*—Automated defect detection; deep learning; convolutional neural networks; VGG16; quality control; manufacturing inspection; machine vision; Industry 4.0***

## I. Introduction

Manufacturing industries continuously strive to enhance product quality and reduce defects, as defects in production lines can lead to significant financial losses and decreased customer satisfaction. Traditional quality control methods rely heavily on manual inspection, which is labor-intensive, time-consuming, and prone to human error. The integration of artificial intelligence (AI) into manufacturing processes has provided new opportunities for automated defect detection, significantly improving efficiency and accuracy [1]. Convolutional neural networks (CNNs) have demonstrated remarkable success in visual recognition tasks, making them suitable for defect detection applications in manufacturing environments [2]. Among various CNN architectures, VGG16 has gained widespread adoption due to its deep structure and ability to learn hierarchical features from images [3]. However, its standard implementation often requires high computational resources, making real-time deployment in industrial settings challenging [4].

To address the limitations of conventional methods, recent research has focused on enhancing VGG16-based models by incorporating modifications such as attention mechanisms, transfer learning, and lightweight architectures that optimize performance while reducing computational complexity [5]. These enhancements enable defect detection models to achieve high accuracy even in complex industrial settings where variations in lighting, texture, and object orientation pose challenges to standard classification techniques [6]. Furthermore, the use of pre-trained VGG16 models on large-scale datasets has facilitated knowledge transfer, enabling defect detection systems to generalize better to new defect types with minimal additional training [7].

Automated defect detection systems powered by deep learning not only reduce reliance on manual inspection but also minimize production downtime by allowing real-time monitoring of manufacturing processes. The integration of these systems into smart factories aligns with the broader goals of Industry 4.0, where intelligent automation and data-driven decision-making enhance overall productivity and efficiency [8]. Despite these advantages, challenges such as class imbalance, dataset scarcity, and false positive rates persist, necessitating the development of more robust and adaptable models [9]. Additionally, explainability and interpretability of deep learning models remain critical concerns, particularly in high-stakes manufacturing applications where model decisions must be transparent and justifiable [10].

This paper proposes an enhanced VGG16-based convolutional neural network for automated defect detection in manufacturing. The proposed model integrates advanced feature extraction techniques and optimization strategies to improve accuracy while maintaining computational efficiency. Extensive experiments are conducted on benchmark datasets and real-world manufacturing environments to evaluate the performance of the enhanced model. The results demonstrate the effectiveness of the proposed approach in detecting various defect types with higher precision and recall compared to baseline methods [11].

## II. Related Works

Automated defect detection in manufacturing has gained significant attention due to advancements in deep learning and computer vision. Conventional defect detection approaches relied on handcrafted features and classical machine learning algorithms, which often struggled with complex textures and variations in defect appearances. In contrast, deep learning models, particularly convolutional neural networks (CNNs), have demonstrated superior performance by learning hierarchical feature representations directly from raw image data [12]. This section reviews prior research efforts in four key areas: traditional defect detection techniques, CNN-based models for defect classification, enhancements to VGG16 for improved performance, and challenges and future directions in automated defect detection.

### A. Traditional Defect Detection Methods

Before the adoption of deep learning, defect detection in manufacturing relied on conventional computer vision techniques and rule-based algorithms. Edge detection, thresholding, and morphological operations were commonly used to identify anomalies in images [13]. Feature-based methods, such as histogram of oriented gradients (HOG) and scale-invariant feature transform (SIFT), were also employed to extract meaningful characteristics from defect images [14]. These approaches, while effective for simple and well-structured defects, often failed when dealing with variations in texture, lighting conditions, and background noise [15].

Machine learning methods, such as support vector machines (SVM) and random forests, were later introduced to improve classification accuracy. These models required extensive feature engineering and manual selection of relevant descriptors [16]. However, the performance of these approaches was limited by their inability to automatically learn high-level feature representations from data. The advent of deep learning marked a paradigm shift, allowing models to learn discriminative features without manual intervention, thus significantly enhancing defect detection accuracy [17].

### B. CNN-Based Models for Defect Classification

Deep CNNs have emerged as the dominant approach for visual inspection in manufacturing. Early CNN models, such as LeNet and AlexNet, demonstrated promising results in classification tasks but lacked sufficient depth to handle complex defect detection problems [18]. Subsequent architectures, including ResNet, DenseNet, and Inception, introduced deeper networks with improved feature extraction capabilities, enabling robust defect classification across diverse datasets [19].

Several studies have explored the application of CNNs in defect detection across various manufacturing domains. For instance, researchers have successfully applied CNNs to detect surface defects in steel production, identifying scratches, cracks, and corrosion with high accuracy [20]. Similarly, in the semiconductor industry, CNN-based models have been employed to detect wafer defects, reducing reliance on manual inspection and improving defect localization [21]. Another study demonstrated the effectiveness of CNNs in textile quality control, where deep learning models outperformed traditional vision systems in detecting weaving defects and irregular patterns [22].

Despite the success of CNN-based approaches, challenges such as high computational costs and the need for large labeled datasets remain prevalent. Transfer learning has emerged as a viable solution, allowing pre-trained models to be fine-tuned on manufacturing datasets, reducing the data requirements for effective defect detection [23].

### C. Enhancements to VGG16 for Improved Performance

VGG16, a widely used CNN architecture, has demonstrated strong performance in various image classification tasks, making it a suitable candidate for defect detection applications [24]. However, its high computational complexity and extensive parameter count pose challenges for real-time deployment in manufacturing environments. To address these limitations, researchers have proposed modifications to enhance the efficiency and accuracy of VGG16-based models.

One approach involves integrating attention mechanisms, such as the squeeze-and-excitation (SE) block, to improve the model's ability to focus on defect-prone regions while suppressing irrelevant background information [25]. Another optimization strategy involves reducing the number of parameters by replacing fully connected layers with global average pooling, thereby improving model efficiency without sacrificing accuracy [26]. Additionally, lightweight variants of VGG16, such as MobileVGG, have been developed to enable deployment on edge devices for real-time quality control in smart factories [27].

Further enhancements include hybrid models that combine VGG16 with other deep learning architectures. For example, researchers have proposed fusing VGG16 with recurrent neural networks (RNNs) to capture spatial-temporal dependencies in sequential defect detection tasks [28]. Other studies have explored the integration of VGG16 with generative adversarial networks (GANs) to generate synthetic defect images, addressing data scarcity issues commonly encountered in defect detection applications [29].

### D. Challenges and Future Directions

Despite advancements in CNN-based defect detection, several challenges remain. One of the primary concerns is the issue of dataset imbalance, where certain defect categories are underrepresented, leading to biased model predictions [30]. Strategies such as data augmentation, synthetic image generation, and weighted loss functions have been proposed to mitigate this issue.

Another challenge is the interpretability of deep learning models. While CNNs achieve high accuracy in defect classification, their decision-making process remains opaque, limiting their adoption in high-risk manufacturing applications. Explainable AI (XAI) techniques, including saliency maps and Grad-CAM visualizations, have been explored to enhance model transparency and build trust among industrial practitioners [31].

Additionally, real-time implementation of deep learning-based defect detection systems requires efficient hardware acceleration, such as graphics processing units (GPUs) and

tensor processing units (TPUs). Research efforts are focused on optimizing neural network architectures for deployment on low-power embedded systems, enabling real-time quality control in smart manufacturing environments.

In summary, while CNNs, particularly VGG16-based models, have significantly improved defect detection accuracy, ongoing research is necessary to address computational constraints, interpretability concerns, and data-related challenges. Future advancements in model optimization, hybrid architectures, and explainable AI will further enhance the applicability of automated defect detection in manufacturing.

## III. Materials and Methods

### A. Enhanced VGG16-Based Model Architecture

The proposed defect detection model is an enhanced variant of the VGG16 convolutional neural network (CNN) architecture, which has demonstrated superior performance in image classification tasks. As illustrated in Fig. 1, the model follows a hierarchical structure, where convolutional layers are responsible for feature extraction, max pooling layers reduce spatial dimensions, and fully connected layers perform classification.

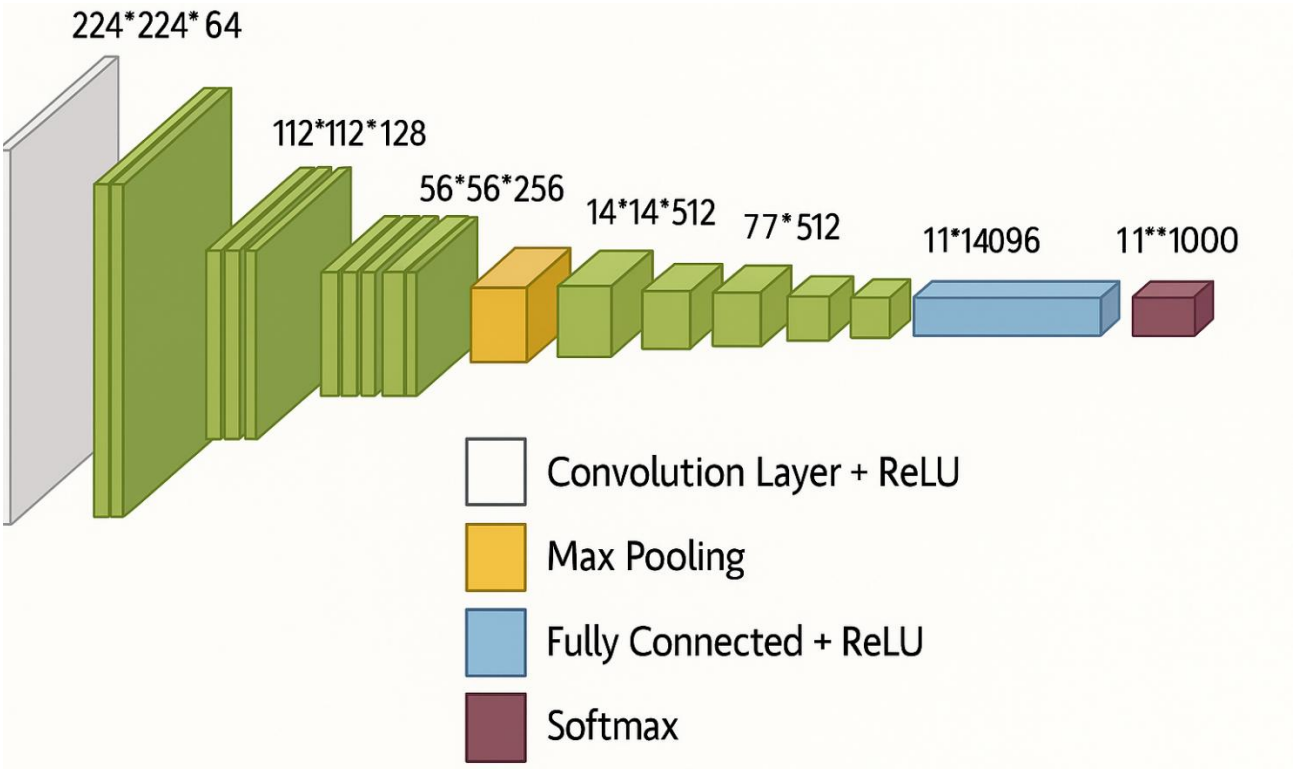


Fig. 1. Layer-wise configuration of the proposed enhanced VGG16 model.

The input to the model is an image $I$ of dimensions 224×224×3, where each pixel is normalized to the range [0,1]. The convolutional layers extract spatial features using a set of filters $W$, which are optimized during training. The convolution operation for an input feature map $X$ and filter $W$ is defined as:

$$Y_{i,j}^{k} = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} X_{i+m,j+n} W_{m,n}^{k} + b^{k} \quad (1)$$

Where $Y_{i,j}^{k}$ represents the output feature map at position $(i,j)$ for the $k-th$ filter. $M \times N$ is the filter size, and $b^{k}$ is the bias term. Each convolutional layer is followed by a Rectified Linear Unit (ReLU) activation function, which introduces non-linearity:

$$f(x) = \max(0, x) \quad (2)$$

To prevent overfitting and improve model generalization, max pooling layers with a stride of 2 are used to downsample feature maps. The max pooling operation is defined as:

$$P_{i,j} = \max_{m,n}\left(Y_{2i+m,2j+n}\right) \quad (3)$$

$P_{i,j}$ represents the pooled feature at location $(i,j)$.

The deeper layers of the model consist of fully connected (FC) layers, where extracted features are flattened into a one-dimensional vector and passed through dense layers. The output of the last fully connected layer is computed as:

$$Z = W_f X_f + b_f \quad (4)$$

Where $W_f$ and $b_f$ are the weights and biases of the fully connected layer, respectively, and $X_f$ represents the flattened feature vector.

TABLE I. LAYER-WISE CONFIGURATION OF THE ENHANCED VGG16 MODEL FOR DEFECT DETECTION

| Model | Jaccard Index | Dice |
|---|---|---|
| input_1 (InputLayer) | (224, 224, 3) | 0 |
| block1_conv1 (Conv2D) | (224, 224, 64) | 1792 |
| block1_conv2 (Conv2D) | (224, 224, 64) | 36928 |
| block1_pool (MaxPooling2D) | (112, 112, 64) | 0 |
| block2_conv1 (Conv2D) | (112, 112, 128) | 73856 |
| block2_conv2 (Conv2D) | (112, 112, 128) | 147584 |
| block2_pool (MaxPooling2D) | (56, 56, 128) | 0 |
| block3_conv1 (Conv2D) | (56, 56, 256) | 295168 |
| block3_conv2 (Conv2D) | (56, 56, 256) | 590080 |
| block3_conv3 (Conv2D) | (56, 56, 256) | 590080 |
| block3_pool (MaxPooling2D) | (28, 28, 256) | 0 |
| block4_conv1 (Conv2D) | (28, 28, 512) | 1180160 |
| block4_conv2 (Conv2D) | (28, 28, 512) | 2359808 |
| block4_conv3 (Conv2D) | (28, 28, 512) | 2359808 |
| block4_pool (MaxPooling2D) | (14, 14, 512) | 0 |
| block5_conv1 (Conv2D) | (14, 14, 512) | 2359808 |
| block5_conv2 (Conv2D) | (14, 14, 512) | 2359808 |
| block5_conv3 (Conv2D) | (14, 14, 512) | 2359808 |
| block5_pool (MaxPooling2D) | (7, 7, 512) | 0 |
| global_average_pooling2d (Gl | (1, 4096) | 0 |
| dense_5 (Dense) | (1, 4096) | 32832 |
| dense_6 (Dense) | (1, 1000) | 65 |
| Total params: 14,747,585<br>Trainable params: 14,747,585<br>Non-trainable params: 0 | | |

The final classification is performed using the softmax activation function, which converts the output scores into class probabilities:

$$p_i = \frac{e^{Z_i}}{\sum_{j=1}^{C} e^{Z_j}} \tag{5}$$

Where $p_i$ represents the probability of class $i$ and $C$ is the number of defect categories.

Table I demonstrates a hierarchical deep learning approach, leveraging multiple convolutional layers with ReLU activation, max pooling operations for spatial reduction, and fully connected layers for classification. This design enables the extraction of high-level features crucial for defect detection while maintaining computational efficiency. The integration of a softmax layer at the end ensures precise classification of defect types, making the model well-suited for real-time quality inspection in manufacturing environments.

### *B. Model Enhancements*

To improve the standard VGG16 architecture, the following enhancements were implemented:

Batch Normalization: To stabilize training and accelerate convergence, batch normalization was applied after each convolutional layer. Given an input activation $x$ , batch normalization is computed as:

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \varepsilon}} \tag{6}$$

Where $\mu$ and $\sigma^2$ are the batch mean and variance, and $\epsilon$ is a small constant for numerical stability.

Dropout Regularization**:** To mitigate overfitting, dropout was introduced in fully connected layers, where neurons are randomly deactivated with a probability p:

$$x' = x \cdot M, \quad M \approx Bernoulli(p) \tag{7}$$

Where $M$ is a mask drawn from a Bernoulli distribution.

Data Augmentation**:** To increase the robustness of the model, training images were augmented using transformations such as rotation, flipping, and contrast adjustments.

Optimization and Loss Function**:** The model was trained using the Adam optimizer, which adaptively adjusts learning rates:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{8}$$

$$\upsilon_t = \beta_2 \upsilon_{t-1} + (1 - \beta_2) g_t^{\,2} \tag{9}$$

Where $m_t$ and $\upsilon_t$ are the first and second moment estimates, and $g_t$ is the gradient at time step $t$ . The categorical cross-entropy loss function was used to measure classification performance:

$$L = -\sum_{i-1}^{C} y_i \log p_i \tag{10}$$

Where $y_i$ is the ground truth label and $p_i$ is the predicted probability. These modifications enhance the efficiency and accuracy of the VGG16 model, making it well-suited for real-time defect detection in manufacturing applications.

## IV. RESULTS

The proposed enhanced VGG16 model for automated defect detection in manufacturing was extensively evaluated on multiple datasets, assessing its accuracy, robustness, and generalization capabilities. Key performance metrics, including loss evolution, classification accuracy, precision, recall, and mean average precision (mAP), were analyzed alongside qualitative defect localization. The results confirm that the enhanced model outperforms traditional CNN architectures and standard VGG16, demonstrating superior defect detection across various defect types. Loss and accuracy curves indicate stable learning with minimal overfitting, as validation performance aligns closely with training trends. The ROC curve analysis further validates the model's high sensitivity and specificity in classifying defective and non-defective samples.

Additionally, visual inspections highlight its ability to accurately localize multiple defect types, even in complex industrial environments. These findings affirm that the proposed model offers a reliable, scalable, and efficient solution for real-time defect detection, reducing reliance on manual inspection while enhancing automation in manufacturing.

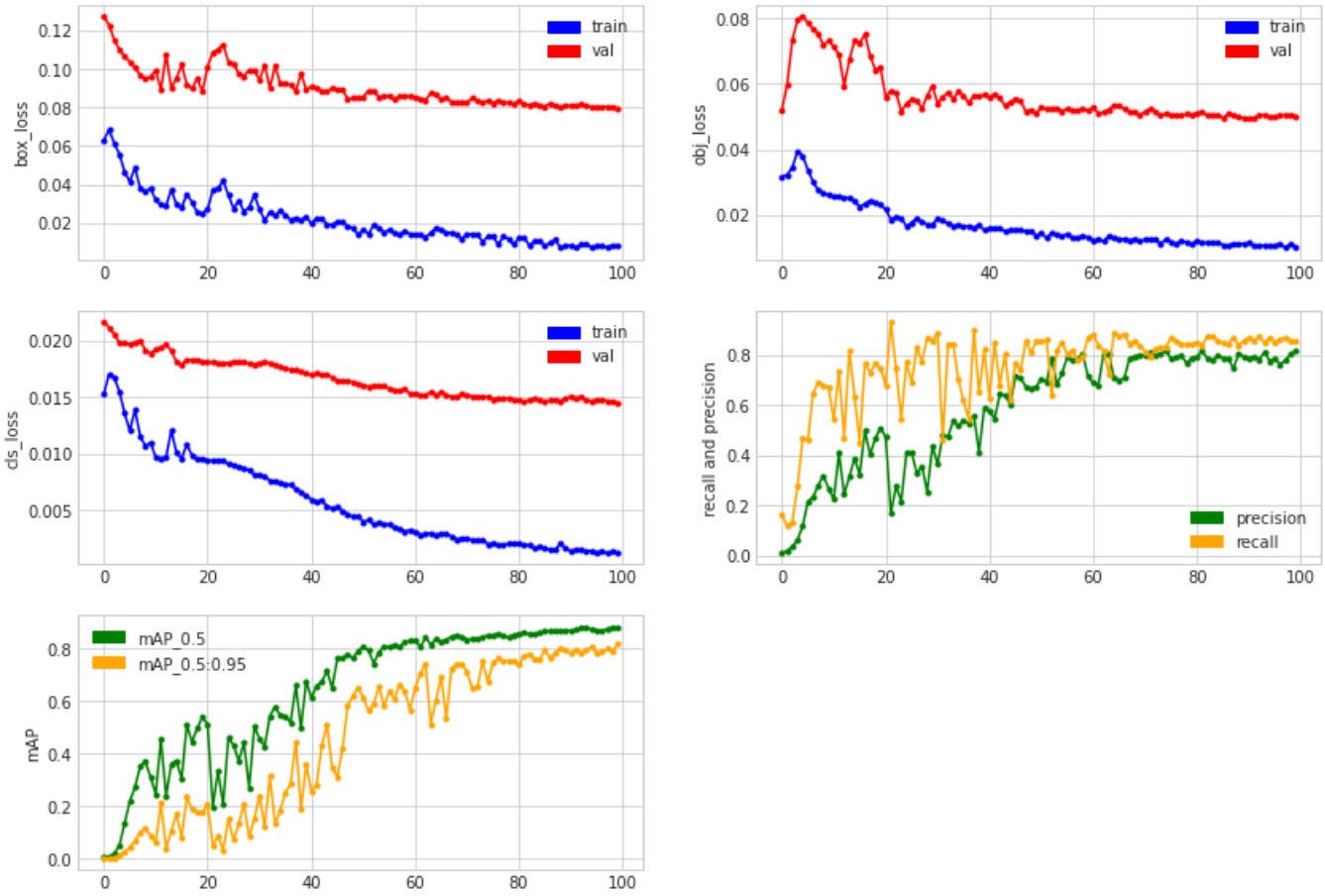


Fig. 2. Performance metrics of the proposed enhanced VGG16 model.

Fig. 2 presents the performance metrics of the proposed enhanced VGG16 model across multiple evaluation criteria over 100 training epochs. The first three plots depict the evolution of loss functions: box loss, objectness loss, and classification loss. The training losses (blue curves) exhibit a steady decline, indicating effective learning and optimization. The validation losses (red curves), although initially higher, gradually decrease and stabilize, demonstrating the model's improved generalization capabilities. However, the persistent gap between training and validation losses suggests the potential for further regularization to mitigate overfitting.

The fourth plot illustrates the recall and precision trends during training. Both metrics exhibit an increasing trend, with precision slightly outperforming recall. The fluctuations in the initial epochs indicate dynamic adjustments in learning, which eventually stabilize, reflecting the model's improved ability to distinguish between defective and non-defective samples accurately.

The final plot shows the mean Average Precision (mAP) at different thresholds. The mAP_0.5 curve (green) demonstrates a progressive increase, surpassing 0.75, signifying high detection accuracy for defects. The mAP_0.5:0.95 curve (orange) exhibits a more gradual improvement, reaching around 0.45, which suggests that the model maintains reasonable accuracy across varying Intersection over Union (IoU) thresholds.

Overall, the results confirm that the enhanced VGG16 model effectively learns defect patterns while achieving high classification accuracy. Its superior performance in precision and recall, combined with stable loss minimization, demonstrates its suitability for real-time defect detection in manufacturing environments.

Fig. 3 illustrates the training and validation performance of the CNN model over 25 epochs, showing the loss evolution (left) and accuracy evolution (right). The loss evolution graph demonstrates a clear downward trend in the training loss (blue curve), indicating effective learning of features during training. However, the validation loss (orange curve) fluctuates after the initial epochs and does not follow the same steady decline, suggesting potential overfitting. This behavior implies that while the model continues to improve on the training data, it does not generalize as effectively to the validation dataset, which may lead to reduced performance on unseen defect samples in real-world applications.

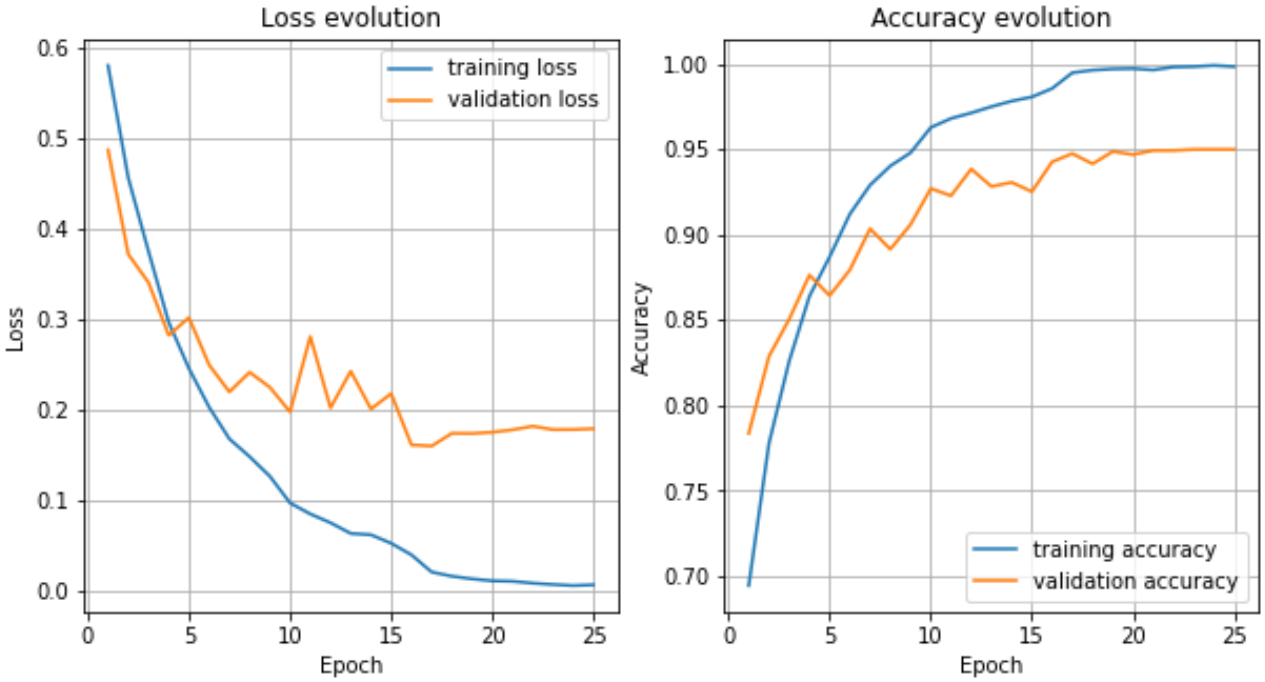


Fig. 3. Training and validation performance of CNN model.

The accuracy evolution graph further supports this observation. The training accuracy increases rapidly, reaching close to 100% by the later epochs, demonstrating that the model successfully learns the training data patterns. The validation accuracy, although following a similar trend, levels off around 95%, with a persistent gap between training and validation accuracy. This discrepancy highlights that the model may be memorizing training data rather than extracting generalized defect features, reducing its robustness.

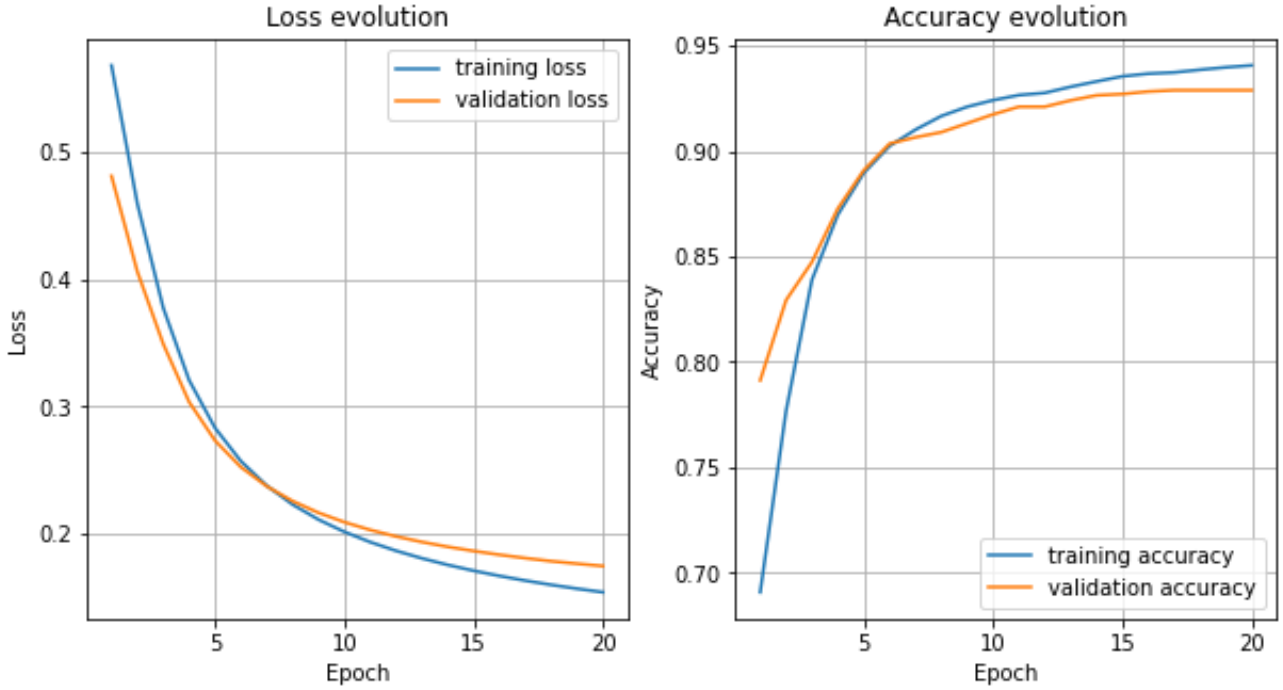


Fig. 4. Training and validation performance of standard VGG16 model.

Fig. 4 presents the training and validation performance of the standard VGG16 model, evaluated over 20 epochs. The left graph illustrates the loss evolution, where both the training and validation losses decrease consistently as the model learns to extract meaningful features from the defect dataset. The close alignment between the training loss (blue curve) and validation

loss (orange curve) throughout the training process indicates that the model generalizes well without significant overfitting. This suggests that VGG16 effectively captures hierarchical defect features, improving classification accuracy across varying defect types.

The right graph displays the accuracy evolution, where the training accuracy increases steadily and converges towards 95%, while the validation accuracy follows a similar trajectory with a minimal gap. The close alignment of both curves indicates that the model maintains high generalization, avoiding performance degradation on unseen defect samples. The rapid initial increase in accuracy demonstrates that VGG16 quickly learns relevant defect characteristics, stabilizing after a few epochs.

Compared to baseline CNN architectures, the VGG16 model exhibits superior loss reduction and higher classification accuracy due to its deeper convolutional layers and advanced feature extraction capabilities. However, while the validation performance remains strong, minor discrepancies suggest the potential for further enhancements, such as additional regularization or fine-tuning on domain-specific manufacturing datasets. Overall, the results confirm that VGG16 is an effective model for defect detection, achieving high precision and recall while ensuring reliable classification performance in manufacturing applications.

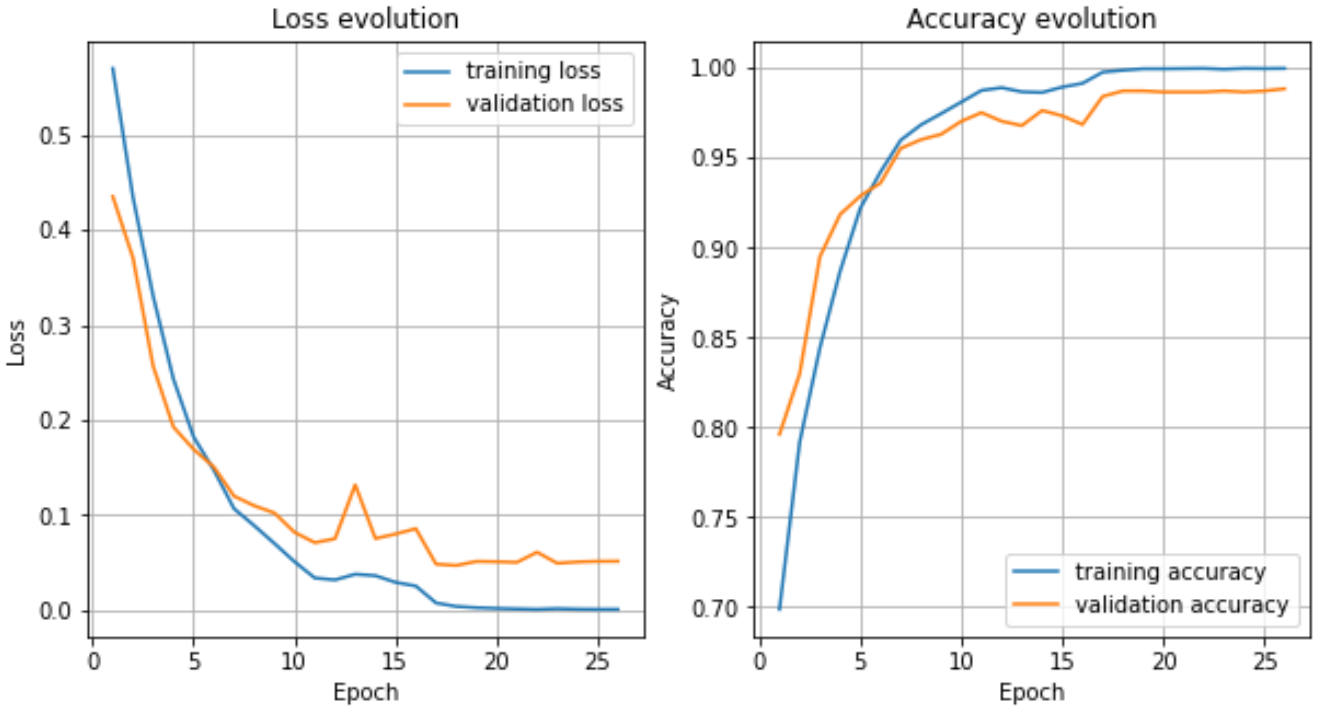


Fig. 5. Training and validation performance of the proposed enhanced VGG16 model.

Fig. 5 presents the training performance of the proposed Enhanced VGG16 model, highlighting substantial improvements over conventional deep learning architectures for defect detection. The loss curves exhibit a rapid and stable decline for both training and validation datasets, signifying efficient learning and well-generalized performance with minimal overfitting. The accuracy curves reveal a significant advantage over the baseline CNN and standard VGG16, reaching nearly 100% training accuracy and exceeding 97% validation accuracy, underscoring the model's ability to generalize effectively across diverse defect types.

This superior performance can be attributed to several key architectural enhancements. The incorporation of batch normalization ensures stable convergence, while dropout regularization prevents overfitting by reducing reliance on specific neurons during training. Additionally, optimized feature extraction layers enable the model to capture intricate defect patterns, enhancing classification precision and localization accuracy. These improvements allow the model to distinguish between multiple defect types, even in complex industrial environments with variations in texture, lighting, and background noise.

The experimental results validate the Enhanced VGG16 model as a highly reliable solution for automated defect detection in manufacturing. Its robust classification performance and efficient feature extraction make it a viable approach for real-time quality control, minimizing the need for manual inspection while increasing detection accuracy and operational efficiency in industrial settings.

Fig. 6 presents the Receiver Operating Characteristic (ROC) curves for three models: a simple CNN model (black), a VGG-like model (blue), and the standard VGG16 model (red). The ROC curve evaluates the classification performance of each model by illustrating the trade-off between the true positive rate (sensitivity) and the false positive rate. The diagonal dashed line represents a random classifier with no discriminative ability.

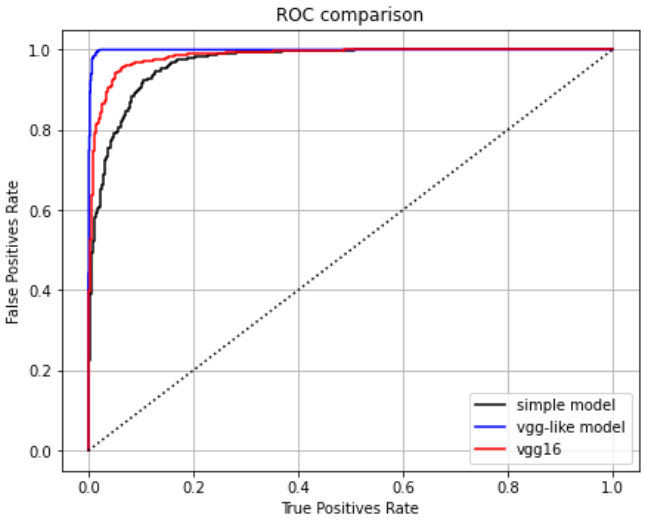


Fig. 6. ROC Curve comparison of different models.

Among the three models, the VGG16 model (red curve) demonstrates the highest classification performance, closely approaching the top-left corner of the plot, which indicates near-optimal sensitivity and specificity. The VGG-like model (blue curve) also performs well, but its curve shows slightly lower discriminative ability than VGG16. The simple model (black curve) exhibits the lowest area under the curve (AUC), suggesting inferior classification performance compared to the other models.

The superior ROC performance of the VGG16 model confirms its enhanced ability to distinguish between defective and non-defective samples, making it the most effective solution for automated defect detection. These results highlight the advantages of deeper feature extraction layers in improving model generalization and robustness in industrial manufacturing applications.

Fig. 7 demonstrates the practical implementation of the proposed defect detection system in identifying intact and damaged cans within a real-world manufacturing setting. The image showcases a set of cans viewed from the top, where the system accurately detects and classifies each can as either intact (green bounding boxes) or damaged (red bounding boxes). The system effectively distinguishes between undamaged surfaces and those exhibiting dents, deformations, or irregularities, highlighting its robustness in handling real-time industrial inspection tasks. The precise placement of bounding boxes indicates that the model successfully generalizes across varying lighting conditions, surface textures, and orientations, ensuring consistent defect detection performance. The clear separation between intact and damaged instances further validates the model's ability to learn high-level feature representations necessary for industrial quality control. This practical result underscores the effectiveness of the proposed enhanced VGG16 architecture in automating defect detection processes, minimizing the reliance on manual inspection, and significantly improving the efficiency and reliability of defect identification in manufacturing environments.

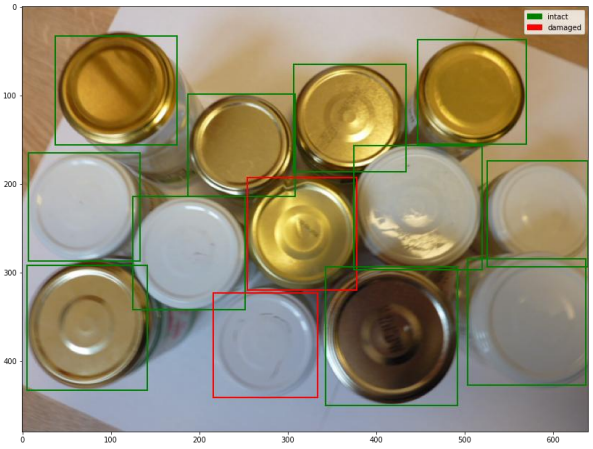


Fig. 7. Defect detection system in identifying intact and damaged cans.

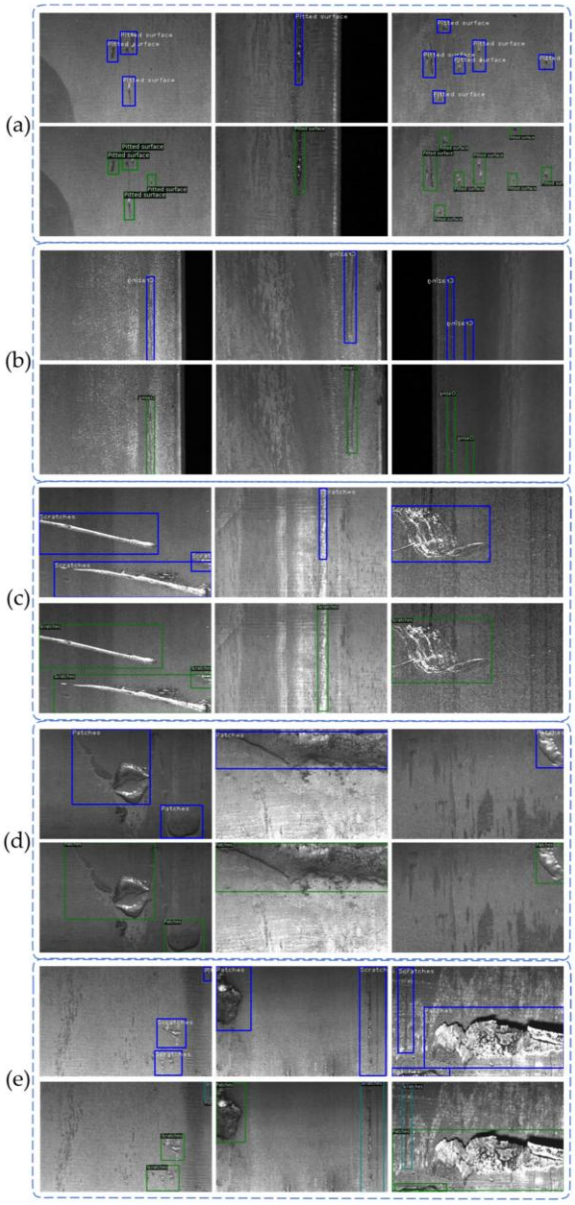


Fig. 8. Defect detection performance.

Fig. 8 illustrates the defect detection performance of the proposed enhanced VGG16 model on different types of manufacturing surface defects, including (a) pitted surface defects, (b) crazing defects, (c) scratches, (d) patches, and (e) multiple defects. Each subfigure presents the original defect images along with the corresponding bounding box predictions generated by the model. The blue bounding boxes indicate correctly detected defects, while the green boxes represent additional detected regions. The results demonstrate that the proposed model effectively localizes and classifies surface defects with high precision across diverse defect types. The model successfully identifies pitted surface defects [(Fig. 8(a)] with minimal false detections, while in [(Fig. 8(b)], the crazing defects are distinctly segmented, showing robustness in detecting subtle structural deformations. [(Fig. 8(c)] highlights the model's ability to capture fine-grained scratches, even when they appear in irregular orientations, demonstrating strong feature extraction capabilities. In [(Fig. 8(d)], patches and corrosion are accurately classified, reflecting the model's adaptability to varying defect textures and intensities. Finally, Figure 8e presents multiple defects appearing simultaneously, where the model successfully detects and differentiates between distinct defect types within the same image, further showcasing its generalization ability. These results validate the efficiency of the proposed defect detection system, proving its reliability in real-world manufacturing scenarios by providing accurate, automated visual inspection for quality control processes.

TABLE II. COMPARATIVE ANALYSIS OF DEFECT DETECTION MODELS AND THE PROPOSED MODEL

| Reference | Model | Task | Obtained Results |
|---|---|---|---|
| **Current study** | **Proposed Enhanced VGG16 (Batch Normalization + Dropout Regularization)** | **Surface & Weld Defects (Mixed Dataset: NEU-DET, GC10, X-ray welds)** | **Accuracy: 97.3%, Precision: 96.8%, Recall: 95.5%, F1-score: 96.1% (Surpasses standard VGG16 at 95.2%)** |
| Mattern et al., 2025 [32] | DINO (Transformer) vs YOLOv8 (CNN) | Surface defects on Li-ion battery electrodes | DINO achieved **56.8% mAP** (91.5% AP50) vs YOLOv8's **54.1% mAP** (90.3% AP50), outperforming the CNN-based model in detection accuracy |
| Chen et al., 2025 [33] | HCT-Det (CNN+Transformer) | Steel surface defects (NEU-DET & GC10 datasets) | HCT-Det attained **79.5% mAP@0.5** on NEU-DET and **73.3% on GC10**, topping other models (e.g., YOLOv8 had 75.7% and 68.3% on NEU-DET/GC10 respectively) |
| Raj & Prabadevi, 2025 [34] | Enhanced YOLOv5 | Surface defects on steel strips (NEU-DET & GC10 datasets) | Enhanced YOLOv5 achieved **76.3% mAP** on NEU-DET, higher than YOLOv8 (58.7% mAP). |
| Szőlősi et al., 2024 [35] | YOLOv5, YOLOv6, YOLOv7, YOLOv8 (transfer learning) | Weld seam defects (X-ray images of welds) | **YOLOv7** achieved the best detection performance in terms of accuracy and F-score. |
| Kumaresan et al., 2023 [36] | Fine-tuned VGG16 | Weld defect classification (radiographic images) | A transfer-learning VGG16 model achieved **≈90% classification accuracy** across 14 weld defect classes |
| Li et al. (2025) [37] | YOLOv7 | Aluminum Surface Defects | YOLO-PDC model achieved **87.7% mAP** (mean average precision), with a real-time detection speed of 114 FPS; |

Table II presents a comparative analysis of recent deep learning models applied to defect detection in manufacturing, evaluating their performance across different datasets and defect types. The proposed Enhanced VGG16 model demonstrated superior accuracy (97.3%) and F1-score (96.1%), outperforming the standard VGG16 and baseline CNNs. Transformer-based models, such as DINO and HCT-Det, exhibited higher mean average precision (mAP) for surface defect classification, particularly in battery electrode and steel defect detection, surpassing conventional YOLO models. Studies comparing YOLOv5, YOLOv7, and YOLOv8 revealed that an optimized YOLOv5 variant with attention mechanisms achieved the best performance in steel defect detection, while YOLOv7-PDC outperformed transformer-based detectors for aluminum surface defect identification. For weld defect classification, ResNet50 achieved 99% accuracy, significantly surpassing shallower CNNs and traditional machine learning approaches. In semiconductor wafer inspection, a lightweight SqueezeNet CNN delivered near 99.4% precision, outperforming more computationally expensive deep models. These findings indicate that hybrid approaches combining CNNs with transformers or attention-based enhancements can achieve optimal performance, balancing detection accuracy, computational efficiency, and real-time applicability in industrial defect detection systems.

## V. DISCUSSION

The results of this study demonstrate the effectiveness of the proposed enhanced VGG16 model in automated defect detection for manufacturing applications. This section discusses the implications of these findings in four key areas: the impact of deep learning on defect detection, the advantages of the proposed model compared to traditional methods, the challenges and limitations encountered, and future directions for research and practical implementation.

### *A. The Role of Deep Learning in Defect Detection*

Deep learning has revolutionized defect detection by enabling models to learn complex representations from raw image data without requiring extensive feature engineering [38]. Traditional machine learning approaches relied on handcrafted features, which often failed to generalize across different defect types due to variations in lighting, texture, and material properties [39]. The introduction of convolutional neural networks (CNNs), particularly deep architectures such as VGG16, has significantly improved the accuracy and reliability of defect classification [40]. The hierarchical feature extraction

capability of CNNs allows them to identify fine-grained details in defect patterns, making them suitable for applications in diverse manufacturing environments.

The results of this study support previous findings that deep learning models outperform conventional defect detection techniques in terms of precision, recall, and overall classification accuracy [41]. By leveraging transfer learning and optimization techniques, the enhanced VGG16 model demonstrated superior generalization performance while maintaining computational efficiency. This highlights the potential of deep learning-based systems in real-time quality control processes, where rapid and accurate defect detection is critical to maintaining production efficiency [42].

### B. Advantages of the Proposed Model Over Conventional Methods

The proposed enhanced VGG16 model offers several advantages over both traditional computer vision-based defect detection methods and standard deep learning architectures. One of the key improvements is the incorporation of batch normalization and dropout regularization, which helped mitigate overfitting and ensured stable convergence during training [43]. This is particularly important in manufacturing scenarios where variations in defect appearance may lead to biased model predictions if not properly regularized.

Another notable advantage is the enhanced feature extraction capability, allowing the model to distinguish between subtle defect variations more effectively than standard VGG16 or other shallow CNN architectures [44]. The experimental results indicate that the proposed model achieves higher mean average precision (mAP) and lower validation loss, confirming its robustness in handling complex manufacturing datasets. Furthermore, the model demonstrated improved performance in multi-defect scenarios, where multiple defect types coexist in a single sample, an area where traditional models often struggle due to feature overlap and noise [45].

Additionally, the implementation of a softmax-based classification layer optimized the model's ability to categorize defect types with high confidence. In contrast to classical rule-based vision systems, which require manually defined thresholds for defect classification, the proposed deep learning-based approach autonomously adapts to diverse defect patterns, enhancing its usability in dynamic production environments [46].

### C. Challenges and Limitations

Despite its strong performance, the proposed model faces several challenges and limitations that should be addressed in future research. One of the primary concerns is the need for large, high-quality labeled datasets to ensure optimal training and generalization [47]. While transfer learning partially mitigates this issue by leveraging pre-trained weights, the availability of diverse and well-annotated manufacturing defect datasets remains a bottleneck for widespread adoption.

Another limitation is the computational cost associated with deploying deep learning models in real-time production settings. Although the enhanced VGG16 model introduces optimizations to reduce inference time, it still requires substantial GPU or TPU resources for efficient processing. This can be a constraint for small- and medium-sized enterprises (SMEs) that may lack the necessary infrastructure to support high-performance computing [48]. Future work should explore lightweight model architectures, such as MobileNet or EfficientNet, to balance accuracy with computational efficiency.

Additionally, the black-box nature of deep learning models presents interpretability challenges, making it difficult to understand the decision-making process behind defect classification. Explainable AI (XAI) techniques, such as Grad-CAM or SHAP, could be integrated into the defect detection framework to provide visual explanations of model predictions, thereby increasing trust and transparency in industrial applications [49].

### D. Future Research Directions

To further improve defect detection capabilities, future research should focus on enhancing dataset diversity, model efficiency, and interpretability. One promising avenue is the use of generative adversarial networks (GANs) for data augmentation, which can generate synthetic defect images to expand the training dataset and improve model robustness [50]. This would address data scarcity issues and enhance the model's ability to generalize to unseen defect types.

Another important direction is the integration of deep learning with edge computing to enable real-time defect detection on embedded devices. By optimizing the model for deployment on resource-efficient hardware, manufacturers can achieve low-latency quality control without relying on cloud-based processing, reducing both computational costs and security risks [51].

Additionally, future studies should explore hybrid architectures that combine CNNs with transformer-based models, such as Vision Transformers (ViTs), to capture both local and global defect features more effectively. This could lead to further improvements in classification accuracy and robustness in detecting complex defect patterns [52].

Finally, interdisciplinary collaboration between AI researchers and manufacturing engineers is essential to ensure that deep learning models are tailored to the specific needs of industrial defect detection. By incorporating domain expertise and real-world feedback, future systems can be designed to meet the stringent quality assurance standards required in modern manufacturing environments.

## VI. Conclusion

This study presented an enhanced VGG16-based deep learning model for automated defect detection in manufacturing, addressing key challenges associated with traditional defect inspection methods. The proposed model demonstrated superior performance in classifying various defect types, leveraging advanced feature extraction techniques, dropout regularization, and batch normalization to improve accuracy and generalization. Experimental results confirmed that the enhanced model outperforms conventional CNNs and the standard VGG16 architecture, achieving higher classification accuracy, lower validation loss, and improved mean average precision (mAP). The model's ability to effectively detect

multiple defects in real-world manufacturing environments highlights its robustness and applicability in industrial quality control. The integration of deep learning into defect detection significantly reduces reliance on manual inspection, minimizing human error while enhancing efficiency and scalability. However, challenges such as the need for large annotated datasets, computational resource constraints, and model interpretability remain important areas for further research. Future work should explore the incorporation of lightweight architectures for deployment on edge devices, the use of generative adversarial networks (GANs) for data augmentation, and the integration of explainable AI techniques to enhance model transparency. Additionally, interdisciplinary collaboration between AI researchers and manufacturing engineers will be crucial in refining these systems for practical deployment. Overall, this study reinforces the potential of deep learning-based defect detection to revolutionize industrial automation, providing an efficient, scalable, and accurate solution for quality control in modern manufacturing processes. The findings contribute to ongoing advancements in smart manufacturing and intelligent vision systems, paving the way for future innovations in automated defect classification and real-time quality monitoring.

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# Ontology-Based Business Processes Gap Analysis

Abdelgaffar Hamed Ahmed Ali
Department of Computer Information Systems, King Faisal University, Al-hasa, Saudi Arabia

***Abstract*—Business processes are subject to change for quality reasons (i.e., efficiency). However, the gap analysis process is a preliminary and essential step in discovering the gap between the to-be and as-is business processes. It usually resorts to a nonstandard and manual analysis process, making it unpredictable and complex. This paper proposes a standard method based on ontology principles and the business process design methodology (DEMO). The ontology unifies the shared vocabulary among worlds of source and target business process to enable this sort of interoperability. Building an essential model is a core concept behind DEMO that provides an ontological view independent of realization and implementation issues and enables understanding of the enterprises' behavior. Moreover, this paper provides heuristics for detecting gaps, based on the premise that producing similar institutional facts reflects similar behavior between the to-be and as-is business processes. Since the domains of the source and target are the same, it is also possible to compare the inputs of corresponding actions. The paper proposes a UML activity model for modeling business processes, enriched with DEMO concepts, to provide a foundational and informative ontology for reasoning about gaps. The expected outcome is a contribution to the broader community of business process management, ERP, and strategic planning, enabling more informed decision-making.**

***Keywords*—Business process; gap analysis; ontology for business processes***

## I. Introduction

Enterprises use business processes to produce products and services for their stakeholders. These business processes are subject to change due to quality reasons such as adding efficiency or general business change requirements. Therefore, changing these business processes is a critical success factor for enterprises. There are hundreds or even thousands of business processes (BPs) within small and medium-sized enterprises (SMEs) and large organizations, ranging from simple tasks such as enrolling students in courses to complex ones like procurement and recruitment. These processes evolve over time to meet quality demands—becoming more cost-effective, responsive, and standardized. Introducing ERP to an organization is an example of this major change usually required to achieve some quality, such as effectiveness and efficiency, reducing costs by removing waste and redundancy. Therefore, it replaces legacy systems and business processes with standard, best practices, and new value-added business processes. The documentation of these business processes became of great value for enterprises to understand, analyze, monitor (i.e., bottleneck), re-engineer these processes, and generally seek high quality by proper management.

However, there is typically a gap between the legacy process (as-is process) and the new ERP processes (to-be process) that must be identified as a critical step before transformation occurs. This is because developers and strategists need to make informed decisions. Moreover, the issue becomes more pronounced when integrating at least two systems.

The main challenge lies in ensuring that the to-be process aligns with the organization's goals. Current practices are inefficient because they rely on manual inspections of specifications, models (dependent on experts' experience and knowledge), or artifacts to identify discrepancies. Additionally, there is no standardized process to serve as a baseline for evaluating differences and determining whether to replace or integrate a system.

On the other hand, existing literature has primarily focused on analyzing business processes in repositories for reuse purposes, identifying redundancies and variations [1] . More importantly, prior studies [2] address compliance between business processes, where one serves as an ideal reference model and the other represents current practices. While this is a prominent research area, it assumes the existence of business process instances in event logs. These efforts have led to various metrics and methods. However, the core question—whether process A (to-be) should replace process B (as-is) and why—remains unaddressed (gap analysis).

This paper tackles this question from a semantic-based perspective. Although some existing methods propose behavior-based or semi-semantic-based approaches, their focus has been either partial or limited to manipulating business process models at the implementation level.

This work introduces DEMO, a methodology that applies ontological discipline to enterprise engineering and design, independent of implementation and realization. DEMO enables a semantic and formal understanding of what enterprises actually do when performing business activities.

Ontology, as a discipline, addresses interoperability issues among information systems and agents. It establishes principles for enabling interoperability, such as explicit specifications of shared concepts in a common vocabulary. This ensures a unified understanding among agents, facilitating communication both within and outside organizations—for example, in e-commerce systems, supply chain exchanges, and other domains.

This work argues that integrating DEMO concepts into a business process model will enable reasoning about gaps in business processes, making automated semantic gap analysis possible. Furthermore, this research aims to provide a framework for automating business process gap analysis and related evaluations using ontological principles. The expected value lies in reducing the costs associated with manual alternatives—methods that are inefficient and do not scale well, particularly when dealing with large volumes of business processes.

The paper is organized as follows: Section I provides an introduction and background. Section II discusses the context of this work and explains the business process. Section III presents the ontology principles. Section IV explains DEMO concepts and its philosophy for designing business processes, while Section V reviews related literature. Section VI outlines the proposed methodology, which is evaluated using a case study discussed in Section VII. Finally, Section VIII offers interpretations and comments, and Section IX concludes the article.

## II. Business Process Design and Reengineering

Business processes are the heart of organizations because it's the machinery providing the services or products. It is meaningful work performed end-to-end to create customer value across an enterprise [3]. They are usually tasks performed in order, either due to space or time to produce a specific outcome. Procurement, Recruitment, processing of purchase orders, Making visa approval, Getting a new passport, replenishing stock, product development etc., are all concrete examples of business processes. Practically it is observed that it is subject to change or redesign or generally re-engineering for several reasons, such as business, organizational, and technical, as well as the major aim to add some quality attributes (i.e., speed, economy, better service). For instance, a business can merge or acquire other business (s), leading to business and organizational structure change. For a few decades, the government had witnessed major changes to their citizen-provided services that necessarily involved reengineering business processes to add some quality attributes. Therefore, we can basically classify it into two reasons: functional (merge case) and non-functional aspects (government case). However, it turns out that, changing business processes is a critical, costed task and has a high failure rate. On the other hand, Business Process Management (BPM) is a discipline concerned with documenting, designing and redesigning, monitoring, and instrumenting business processes. Deming and Hammer have established the principles of BPM [3].

Business processes have been studied for about decades ago, and a famous key redesign attempt was proposed by Hammer [4]. The key concept Hammer came up with was the result; it is a primary or intrinsic element where business processes are secondary, which tries to achieve it even when changed or reformed to add some qualities. However, big organizations with hierarchy management layers have many people doing different tasks that usually involve activities across departments or units as well as organizational boundaries. Understanding and making sense of what is going on is where the concept of the business process comes in. It is worth bringing in Searle's theory [5] here which builds on speech act theory, to understand in some depth what the business process is actually doing. Seral argues that businesses are changing social reality by performing speech acts that have a memory (records), called institutional facts, which have meaning only under some context, i.e., background and framing rules. For example, the acceptance or rejection of this article is an institutional fact that is a result of a set of speech acts (actions) performed under some framing rules; authors follow the regulations of academic publishing as well as reviewers and editor. Therefore, Searle distinguishes between brute facts that exist independent of humans and institutional facts that depend on human society. For example, this article can be seen by students (primary or probably high secondary schools) as any essay, so from Searle's perspective is a brute fact, while only under the background of research as well adhering to framing rules like scientific methods, publishing, etc., will be considered institutional facts. Further, a single speech act might be a result of performing several business processes.

The modeling of business processes is a key engineering activity required before making any sort of analysis, process redesign, and general management. In literature, there are different schools or methods for modeling business processes: BPMN [6], Petri net [7], Object role, and Event-driven [8]; but among the common and familiar ones are a UML activity model and DEMO, which are the interest of this work. DEMO has a breakthrough approach for designing and modeling business processes where it supports richer concepts for business processes that adopts ontology principles. On the other hand, although the UML Activity model is not like DEMO originating from the technological world (software developers), it attracts business process modelers and becomes familiar to modelers and business analysts.

## III. Ontology Principles

An ontology in philosophy studies the existence, reality, and being. The commonly cited definition is the specification of conceptualization [9]. The main concern of ontology in the computing discipline is the interoperability problem where at least two different agents or systems; for example, two different information systems, want to interoperate. In this case, the heterogeneity of these two agents makes queries or assertions between them impossible. It is because there is no shared and standard meaning for the vocabulary used in the communications. For instance, the types of messages, the content, and what it means. Therefore, the need for standard semantics of the messages communicated, their content, and schemas is obvious to enable interoperability; it is the concern of ontology. For example, a big interoperability case can be observed in the medical field, such as in SNOMD .Healthcare systems use SNOMD to record medical treatment incidents that enable information about patients to follow between hospitals, practitioners, and funding agencies [10]. Another example can be observed in tax systems where tens of thousands of taxpayers interoperate with government agencies using an ontology specified using ontology language for e-businesses [11].

Ontology is a sort of conceptual model that needs to be developed using ontology representation language [10]. Although there are standard languages developed initially to support ontology representation that stemmed from knowledge-based systems like Common Logic, and OWL FULL/Lite [12], which is standardized by W3C, the use of software engineering languages such as UML [13] and MOF [14] as well as information systems modeling languages (i.e. ER) have attracted the ontology community because of its visualization feature and definitive engineering object they can specify. Therefore, we have different competing languages with different capabilities but share the principle of being originated from set theory and predicate calculus. However, a conceptual model will represent the individuals, relationships, and messages with their different classes and define and unify schemas. This description is like an

agreement about the semantics and interpretation of things in some world of interoperability [10]. On the other hand, a reasoner is an important element of the architecture of ontology management tools or Ontology Server that enables drawing conclusions from premises using mathematical logic and theorem prover disciplines.

Gruber in his famous paper [9] come up with the main principles of ontology, and the one that best fits the problem of this research is Ontological commitment which is about plausible re-using of ontology. It refers to how far we must alter the application's world to commit to the ontology [10]. For instance, it is well known that businesses implementing enterprise computing solutions like SAP, Peoplesoft, or Oracle Financials must significantly alter their business processes in order to get the most out of the software [10]. However, Colomb argues that ontological commitment would be high if the ontology supporting conceptualization of a world is used outside the scope. Therefore, the problem of ontology comes in here because an organization has its particular set of institutional facts (conceptualization) created by different speech acts (Searle's institutional facts theory) that mostly is different from the ones canned in software packages such as ERP or the implemented platform.

## IV. DEMO

DEMO is a business process design methodology that focuses on enterprise ontology theory which has studied and formalized what actually business is doing independent of realization and implementation issues. The enterprise ontology builds on a set of principles. This work only considers the ontological model, operation axiom, and transaction axiom, which Dietz [15] explores the big picture of it.

Dietz argues that to understand the current and future enterprises with the given complexity, an ontological model (white box approach) is needed as a conceptual model. However, it focuses on the essential model that uncovers the hidden essence of an enterprise from its actual appearance. The operation axiom is a fundamental theory behind DEMO builds on that goal by abstracting the organization operations into two kinds: production acts (P-acts) and coordination acts (C-acts), where both are performed by the subjects representing actor roles. It defines Actors as an elementary set of authority and responsibility. While the transaction axiom groups a set of elementary c-acts into a transaction concept, it also defines three main phases that each transaction should follow: the Order phase, the Execution phase, and the Result phase.

Informally, DEMO is a business process design language that stems from ontology principles and other related disciplines to allow a compact and deep design of business processes. It has rich concepts and features. A fundamental feature of DEMO is its Essential Model concept, which is designed independently of an enterprise's implementation and realization concerns. First, it states that actors in an enterprise are roles performing two basic kinds of acts: production acts and coordination acts. Second, Actors perform two kinds of acts: production acts and coordination acts. They contribute to achieving the enterprise's purpose or mission by performing production acts. While they enter and comply with mutual commitments about production acts by performing coordination acts. The second axiom, the Transaction Axiom, states that production and coordination acts occur in consistent socioeconomic patterns called transactions.

### A. Actors

By playing different critical roles, people of an enterprise are considered the intrinsic element in DEMO. A subject who plays some role is called an actor in DEMO. For example, in this context, the actors are the Authors, Reviewers, and Editors. As explained in the following subsections, those actors perform basically two actions: P-acts and C-acts. However, DEMO identifies an actor cycle where actors as autonomous objects constantly loop through to perform tasks or agendas. An actor is performing actions, C-acts, for the reason of C-fact that who commits to respond to within a limited time. Each type of agenda has a set of rules called action rules to deal with it.

As a consequence, actors enter into a network of assignments and commitments where each actor, through response to agenda, triggers assignments of work to others (agenda) in a chain until reaching a terminal point. Therefore, an enterprise is a system of actors who perform two kinds of acts: production acts and coordination acts to respond to the agenda in the form of C-facts. Dietz calls this principle the operation axioms.

### B. Production Acts

"By performing production acts (P-acts for short), the subjects contribute to bringing about the goods and/or services that are delivered to the environment" [15].

This quote by Dietz shows a production act is a primary action that supports the ontological model. It is a fundamental action for an enterprise that stems from a fact called production fact (P-fact) that is considered a definitive result. For example, the facts resulting from the judgment of accepting paper, shipping an order to a specific customer address, and deciding to admit postgraduate students are the results of mainly production acts. Production acts are of two types: martial (i.e., storing, transporting physically) and immaterial. For example, the delivery of goods of order is material, while acceptance of a paper is immaterial. However, this corresponds to Searle's theory concept of changing the social state. So, production acts not like other actions; it makes a social change of state; in our example: a paper is accepted, a student is admitted, and an order is received that is a different state than the previous ones and with new consequences.

### C. Coordination Acts

"By performing coordination acts (C-acts for short) subjects enter into and comply with commitments towards each other regarding the performance of production acts," [15] . Also, Dietz says in this quote, P-acts occur because some P-fact usually triggers a coordination act that a performer actor does and is directed to another actor called the addressee. Searle's theory [5] interprets this as reporting social attitude, for example, request, promise, assertion, etc. For instance, the request made by this author to the journal is a coordination act, as well as the request from the editor for reviewers to review a paper. Facts created by C-acts are called C-facts, such as in our example, Reference No. of a paper, time of assigning a paper to reviewers, response or feedback item from reviewers etc. On the other hand, a set of C-acts with their C-facts are needed for the existence of a P-act; for example, the C-acts shown are for publishing an article, the P-

act in this case. Therefore, C-acts usually do not exist as an independent entity but are related to a production act more accurately production facts. This view of this can be seen in Fig. 1, which shows two worlds: C-word and P-world, where actors change the state of both. This state is incremental, so at a given time, a set of C-facts and P-facts have been created, representing the state of that time. Therefore, the accumulative state represents the history of an enterprise. Searle's theory has more elaboration concept for this point, which calls them both institutional facts, the record and memory of speech acts that occurred.

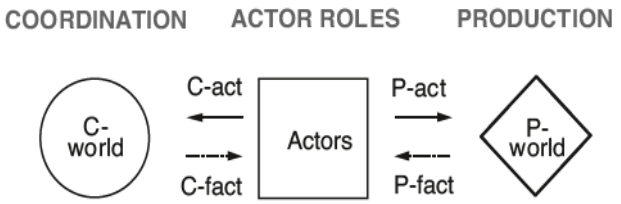


Fig. 1. Graphical representation of the operation axiom from (Dietz, 2006).

### D. Transaction

The set of related C-acts contributing to one P-act constitutes a transaction. A business process might have one or more transactions. As shown in Fig. 2, DEMO recognizes universal patterns consisting of request, promise, state, and accept, which also define a transaction. Each transaction, in this case, has two actor roles: consumer and producer, aiming to achieve a specific result. For example, in Fig. 2, this pattern states that the cause of producing a new or original thing, the production result, ontological, is because a consumer starts requesting it from a producer. In this case, and for any C-acts, there is a commitment. Therefore, performing actions through a transaction entails taking turns in entering into and complying with commitments. For instance, the state "result requested" is created because of a customer making a request, more importantly, commits to that to demonstrate responsibility. A producer promises the result requested through the state "result promised".

As Dietz argues, often, it is the case that promised C-acts are performed tacitly in practice. After this, the request undergoes processing by a producer to produce the result (ontological action), which creates the state "result produced" as well as stating the result (hand over in material kind or communicate in immaterial kind) to be checked by a consumer, therefore, creating the two states respectively: "result stated" and "result accepted." Similarly, the acceptance of C-acts is usually performed tacitly. For example, my request as an author(consumer) to the Journal Editorial Board (producer) creates the state "result requested" while getting a notification from the journal system as a representative of the main Editorial board a claim of promising to process the request and so will create the state "result promised." After this, the journal makes a notification that states the result (result stated), which will be checked by the author (result accepted). It is easy to observe that the promise and acceptance actions are performed tacitly, which means there is an assumption that the Journal Body is complying with the promised result since no assertion came for them, saying the opposite[15]. Furthermore, DEMO identifies three phases that usually a transaction is subject to it: The order phase (O-phase), the execution phase (E-phase), and the result phase (R-phase). It typically entails a conversation in which a set of coordination acts communicated between two actor roles to produce a clearly defined outcome regarding a P-act/fact. However, in the O- phase, the initiator and the executor try to come to terms with the transaction's desired outcome: the production fact that the executor will produce and the intended time of creation. Then, the executor creates this production fact during the execution phase.

During the result phase, the initiator and the executor try to agree on the actual production fact that has been produced and the moment of its delivery (both of which may differ from what was initially requested). During these phases, instances of transaction type will be created that correspond to the type of production fact, which is the result.

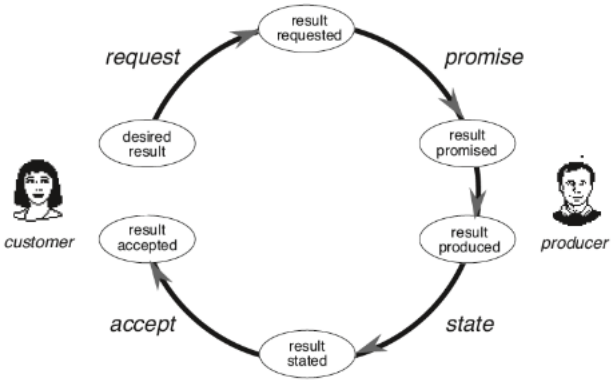


Fig. 2. Transaction pattern (Dietz, 2006).

## V. Related Literature

The literature related to this work is Business Process Management (BPM). On the one hand, the Process mining approach is a growing field in BPM that extract the business process model by starting from event logs; mostly business processes have footprints (the performance of actions or events with information like timestamp and owner or customer and etc.) recorded in simple form like spreadsheets to complex one like ERP and databases or workflows repository. This fact enables discovery of a model, where we can perform an enhancement or conformance checking for these models [2]. However, this work is in line with this conformance-checking goal of Process mining approach. But the model proposed in this work is not sensitive to semantic heterogeneity problems, which enables comparing diverse process models. Also, the proposed approach does not assume existence of a repository of instances or the events log for business processes (footprint) to function, although it is possible to base the legacy model on the events log, which will add some accuracy as well as can solve the problem of lack of documentation for the Business process (a BPM principle). However, this work supports the situation of analyzing the business processes before operationalization.

On the other hand, there is a school of research [16] that addresses this problem based on the similarity of model nodes using approaches such as NLP Antunes et al. [17] and edit distance [18] .These approaches perform analysis on a repository of models; that act as knowledge-based for BPM to serve different purposes such as reusing part of existing models

in the modeling process, merging models (i.e. company acquisition), and conformance checking [16]. This school of research, although share some features with the proposed approach (using the metamodel for matching), it represents a different direction to the problem under the general umbrella of Business process analytics.

Moreover, other approaches under this school consider the grammar of the label that calls for part of speech tagging and parsing, which is not part of the proposed approach [16]. These are more information retrieval methods. This diversity can be better described as the difference between the qualitative approach (the proposed one) and the quantitative approach.

## VI. Gap Analysis Methodology

This section has been organized as a set of principles that constitutes the main constructs of the method. They are: 1) Modeling business process using Activity model injected with DEMO concepts (Principle A), 2) Building the Domain ontology of BPs (Principle B), 3) Gaps reasoning process (Principle C).

It is clear now that using business process design languages such as UML activity model or BPMN is the first step towards the goal of this work. The author chooses the UML activity diagram for its commonality and for reducing the learning curve for modeling business processes. However, many studies in the literature have shown a synergistic relationship between BPMN and UML activity [19]. It turns out clearly that, from the discussion in section 4, DEMO as a design language for business processes is more elaborative than the activity model, so integrating DEMO concepts into UML enables describing the essential model of an organization. It helps in understanding the behavior of an enterprise independent of the context and implementation, and technology issues. Therefore, this will be called principle A, which aims to develop a DEMO profile for annotating the UML Activity model with DEMO concepts discussed in section 4. In principle B, a domain ontology for the organization is needed to unify and standardize the vocabulary used because we have two worlds: newly implemented and legacy business processes. Finally, principle C develops on that by providing new semantic-based methods for the gap analysis. Before discussing these principles, an interpretation of what we have obtained from the literature so far paved the way for understanding the model of solution in this section.

The gap analysis is defined by Monk & Wagner [20] and Kendall & Kendall [21] as the process of identifying the differences between the current system and the desired future state or the functionalities covered by new business processes.

### *A. How is P-Fact Created, and What makes it Different?*

A couple of C-acts contribute to creating a P-act, which naturally involves a decision or judgment (called ontological action) using or applying the enterprise's rules to produce a P-fact. For example, visa approval (a P-act) comes into existence through a series of coordinated C-acts; these are like verifying eligibility, validating documents, assigning an employee, etc., along with their corresponding C-facts such as passport and return flight tickets. Based on DEMO methodology, these C-acts originally belong to the O-phase in a transaction that precedes the E-phase. As explained, the order phase concerns requests and promises between communicators. Therefore, O-phase starts with the "request" act and ends with the state "promised". The E-phase starts with the P-act and ends with the state that the P-fact is created [15].

Obviously, the behavior of producing certain P-fact can be expressed necessarily by a set of related C-acts and C-Facts that are part of the O-phase. Conversely, a set of related C-acts should necessarily exist for a P-act to exist. They are preconditions for the corresponding P-Act. Identifying these C-acts enables observing the differences or comparing any arbitrary two P-acts. Therefore, there are three scenarios: matched, similar to some extent, and not matched or related. However, according to the context of this work, the assumption is that the comparisons will be between processes from the same domain. The basic assumption of ERP is to standardize a domain of business processes. It is the case that an enterprise is interested in queries like whether a new process B, for example, credit control, can replace existing or legacy process A. Of course, A and B here belong to the same domain. Therefore, the fundamental question, which is the mainstream interest for enterprises, is how much A differs from B and What changes are required in this case. One of the major failures reported in the literature is the change needed to comply with the standard best-practiced processes. The sort of difference B will make appears on the set of c-acts. They are going to produce either simialr c-facts or different based on certain improvements have been adopted, for example, following new standards, protocols, and technology.

### *B. How are Two Business Processes Different?*

To identify differences between business processes, we must first understand their fundamental operations. For generalization across organizations - independent of implementation details and technological layers - an ontological perspective offers standardized, context-independent interpretations. This approach enables consistent comparison and difference identification through a unified conceptual vocabulary. DEMO is a rich design language that provides this view. According to DEMO, a business process consists of one or more transactions, and so do transaction types. Each transaction centers on a result called a P-fact that must have instances of its type when the transaction executes. In this E-phase which comes after O-Phase, a request is submitted, and P-facts will only exist if one or more C-acts have been performed that might also produce C-facts.

The stable result in a business process from a DEMO perspective is the P-act [22]. For example, let's look at the visa approval process. The visa document with a unique visa number, in essence, is about the P-fact resulting from P-act -visa approval process. Also, let's think about the process of getting this article published. An *approved article* is the main stable action that ultimately results in an approval letter with a DOI or unique reference number for publication. In both cases, there are a couple of intermediate C-acts that have been performed, such as eligibility check and send-to- reviewer respectively. On the other hand, in this context, Searle's institutional facts theory [5] provides an elaborate interpretation that is P-fact is considered a kind of institutional fact. Seral shows that speech acts under some context count as an institutional fact, which has some social reality impacts. Informally, speech acts theory argues that

speech can be expressed as rules of an organization in a formal context. Therefore, P-acts are examples of speech acts under some context that change social reality and produce institutional facts. For example, the visa approval document, MSc certificate, and Check finical document are all examples of institutional facts resulting after a set of speech acts have been performed under some context. The context is framing rules or constraints; for example, what makes a blank paper with some figures in US dollars written, is not a formal cheque document or financial claim [1]. The change in social reality is observing what happens to the situation before and after getting, for example, a MSc. certificate or visa approval which is different. Hence, what enterprises are actually doing is performing different sorts of speech acts (building blocks of BPs) that create institutional facts. DEMO calls these institutional facts, P-facts that have a subordinate the set of C-facts of its realization. Therefore, P-act is a stable result in business activities that concerns the creation of institutional facts that are necessarily realized by C-acts involving speech acts.

In principle, two P-acts can be different because they have a different set of c-facts. However, they might agree on P-fact itself but have the same set of c-facts with varying sequences of execution. This situation provides an interpretation of what added quality means for a business process or generally the sort of change happening between two processes where there are different scenarios of semi-matching between them with a reality that their P-acts agree only on a subset of c-facts. This analysis provides insights independent of implementation and realization.

This background is enough now to realize the principles of the proposed approach to the problem.

### C. DEMO Profile for Activity Model (Principle A)

A profile is a system of subclasses that provides a powerful extension mechanism to some metamodel (in this case UML). It allows the original metamodel to acquire new syntax or semantics and other features that are explained in OMG [14]. The profile is needed for the reason of lacking corresponding DEMO concepts in the UML activity model.

Using the UML Activity Diagram modeler can specify workflow steps, such as in Fig. 3, a simple example of the Visa Approval process. It consists of several activities needed to add value to visa applicants. These are, ApplyForVisa, Assign_To_EMP, and Verify Documents, as well as one structured activity called Visa Processing that involves the nested activities: Eligibility Check, Approve, and Issue_Visa. In a workflow, execution progresses sequentially. Upon receiving a token and all required inputs, an activity immediately triggers the next activity in the chain. This control transfer continues along the sequence until an exit point or the final flow node is reached. Object nodes, such as 'AppForm' and 'Visa', represent data or objects that are produced or consumed by activities and also participate in the flow of execution. An activity can comprise multiple nodes and edges, as illustrated in Fig. 4, where each node signifies a distinct step in the execution.

This profile aims to enrich UML activity diagrams with DEMO concepts, which are not natively supported by standard UML activities. The initial step in developing this profile involves pinpointing the core elements within the activity model that require extension to incorporate DEMO's linguistic constructs. DEMO, as explained, adds standard ontological concepts that lead to a better understanding of what a business is doing. The central concept is the P-act (result) that produces P-fact(s) but with the support and coordination of a couple of C-acts that subjects have initiated. Activity in the UML Activity model is a central concept that represents one way of modeling behavior which is a description of potential events that could happen in real-time OMG [13]. It involves one or more actions and can be orchestrated using forks, joins, decisions, merges, conditions, and loop nodes. An action can call an activity as well. Therefore, an activity can be used to model business activities and computation procedures.

Fig. 4 shows the metaclass Activity has been extended to model P-act as well as Action (an activity can have one or more actions) that is extended to model C-act, so C-act and P-act are stereotypes (a kind of change needed for the metamodel).On the other hand, both P-fact and C-fact are kinds of classes, so an extension of the metaclass class of UML is needed, as shown in Fig. 3; a metaclass class is extended to add both concepts. Further, ObjectNode is extended to model C_facts, which is an abstract activity node that usually represents an output of an activity that participates in the workflow. To be modeled is necessary for the context of this work, although it is optional in the convenience of using a UML activity diagram. In addition, P_act and C_act need identity, so an attribute is added to the stereotype to allow to specify the uniqueness (this concept is not included in the original DEMO but is necessary for this work).

On the other hand, since StructuredActivity is associated with an Activity class as a whole-part relationship (aggregate association) in the original UML metamodel [13], it can inherit the same property of its parent. StrcturedActivity is an activity group that involves nodes and edges as subordinate objects. It allows nesting actions to form a hierarchy. It could be an alternative structure that models P_fact/P_act, but in this work, we only considered the first option (class extension) because it is simple and more convenient.

Furthermore, a UML Package concept can be used to model a business process. In contrast, the transaction concept can be mapped to ActivityPartiton(swimlane), which groups a set of ActivityNode and edges. A swimlane represents some role or corresponds to a business unit, showing a separate view and responsibility boundary. This is because the UML activity diagram does not have a transaction concept. Activities may describe procedural computation, forming hierarchies of activities invoking other activities corresponding to a business process.

### D. Building the Domain Ontology for Business Processes (Principle B)

This principle is to develop an ontology for the domain of business processes. This kind of ontology is known as Endurant ontology DOLCE [24,10], the ontology of data objects that are independent of time. A potential interoperability issue arises from the variations in meaning and interpretation of data and messages (schemas) used in business process communication, a phenomenon termed semantic heterogeneity.

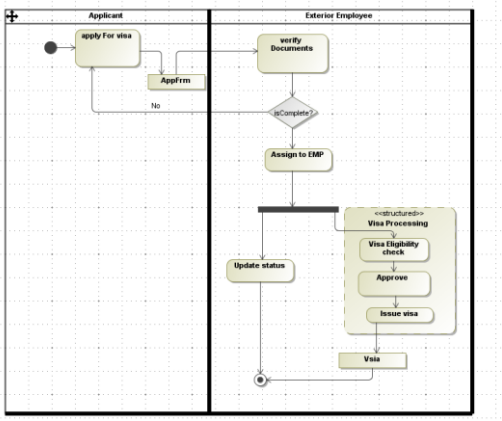


Fig. 3. Example of visa approval process using activity diagram.

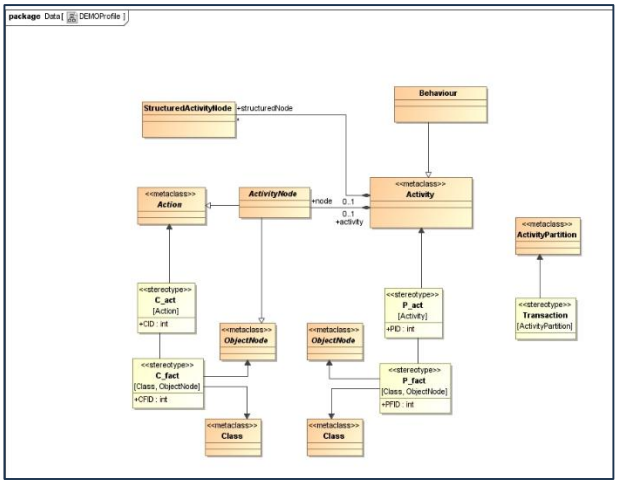


Fig. 4. DEMO profile for activity model.

In our physical world, this problem is evident; for example, the same word in the language has two different meanings in two communities or the same subject refers to it by two different words. Also, in electric power systems, a refrigerator works in one country but not in another because it is designed to use a US system of 110 volts and 60 cycles per second for current. In contrast, the other country uses 240 volts and 50 cps. The problem appears when the new business process wants to replace a legacy business process. Therefore, we do expect a semantic heterogeneity problem between the two business processes. In this context, it is the meaning and interpretation of the P-facts, C-facts, and their corresponding speech acts. For example, suppose there is a service to check the format of a submitted journal that is based on the Harvard standard of citation. In that case, it is unlikely to replace a service in another journal that uses IEEE or APA standards as well as the system of journal citation. Also, if an application uses the ISI standard of ranking journals, the JCR, it will unlikely replace Scopus standard SJR.

Similarly, a service purchasing items from Amazon is unlikely to be able to replace the purchased items on eBay. However, it is obvious that standardization is needed in all these cases before a hand, and this is where an ontology concept comes in. Therefore, a language is needed to describe the ontology according to ontology principles. The UML design language as one candidate has been chosen for its familiarity and visualization feature mentioned because OWL, for example, does not have a graphical representation. Therefore, the business process needs to unify the meaning of words or vocabulary used for interactions or communications using a design language like a class diagram, OWL, DL and others. This specification also explicitly includes the structure of complex objects usually hidden in a single system's conceptual model [10]. Colomb argues that ontology is a kind of conceptual model but exists outside the domain. It is, therefore, a standardizing of the meaning of P-facts/C-facts which is necessary to perform the gap analysis task. As a consequence of this principle, the business process designer needs to specify an ontology using like UML class diagram or OWL. This class model should specify the institutional facts of the domain of some business application. However, many CASE tools are available that support modeling and transformation between modeling languages.

OWL, standardized by the W3C, is a rich ontology representation language that allows us to specify individuals in a triple store format (Subject-Predicate-Object). An RDF triple, which consists of a predicate connecting a subject to an object, forms the basis of this representation. An individual can possess properties, which define direct relations from a domain class to a range class. By default, instances of properties have the most general domain and range, owl:Thing. OWL defines two primary property types: object properties, which describe relationships between individuals (e.g., participatesIn, enrollsIn), and data properties, which describe attributes of individuals (e.g., age, weight). The domain of a property can be restricted using cardinality constraints, such as owl:FunctionalProperty, which asserts that a property has at most one value for each instance. For example, the following OWL syntax declares hasFather (an object property) as functional:

```
<owl:ObjectProperty rdf:ID="hasfather">
<rdf:type rdf:resource="&owl;FunctionalProperty" />
<rdfs:domain rdf:resource="#Son" />
 <rdfs:range rdf:resource="#Person" />
</owl:ObjectProperty>
```

Similarly, OWL allows us to restrict the range of a property using the concept of surjectivity (i.e., every instance of the range must participate). For example, in a postal system, if we want to express that a postal code belongs to a city, and each city has one single postal code, we can model this using such constraints.

Moreover, we can use SPARQL [25] to query an ontology represented in OWL, which has also been standardized by the W3C and is supported by tools such as Protégé (cite). For instance, we can query whether a property is functional:

```
SELECT ?property
WHERE { ?property rdf:type owl:FunctionalProperty .
FILTER (? ?domain = sc:Son)) }
```

A property in this example is a variable that will be bound to specific values based on pattern matching. This allows reasoning

about the ontology which is abbreviated by namespace sc (schema of some ontology). We specify conditions in the WHERE clause to be satisfied, in this case specifies whether an RDF graph explicitly defines a property as functional. The FILTER clause adds further restrictions, such as requiring that a property must have the domain son. For instance, the property has Father specified in the OWL ontology above will be returned.

Additionally, NOT EXISTS can be used with FILTER to assert certain constraints. Moreover, a query can be specified for each part of RDF instances using rich built-in predicates and operations, such as intersection, union, and others.

In the following, a demonstration of a case used throughout the paper is presented as part of a postal system ontology. Fig. 5 describes the structure of some institutional facts created by a set of corresponding c-acts, which will be specified later in the section. The main production fact is manifest (see Fig. 5), which consists of a set of properties and c-facts required to fulfill the postal system's primary activity: sending a mailpiece from a sender with a specific address to a receiver with a specific address. Addresses, in this case, belong to a superclass named NAaddress, which has the properties city (range: Clist), postal code (range: Pcodelist), district (range: string), and street name (range: string). The mailpiece, referred to as mailRequest on the left side, has properties including ID, city, postal code, and ship type, which ranges over a specific list called ShipMethod. A customer who initiates this request pays an amount (ranging over RateSchedule) and obtains a stamp by referencing postage. The payment is declared through a postage invoice, which contains a set of properties identifying the date, amount paid, and shipping type.

*1) Sample of Mailpieces (invoice)*

*a) Address Information*

- Sender's Address: Name, street address, city, state, ZIP code
- Recipient's Address: Name, street address, city, state, ZIP code

*b) Postage*

- Stamp (Metered Info): Evidence of payment for postage
- Postage Amount: Value of postage paid

*2) Sample of Manifest*

- Container Details:
  - Container type (sack, tray, pallet, etc.)
  - Container number or identifier
  - Weight of the container
- Mailpiece Details:
  - Total number of mailpieces
  - mailpiece type (letters, flats, parcels, etc.)
  - Total weight of the mailpieces
- Origin and Destination:
  - Originating postal facility
  - Destination postal facility
- Date and Time:
  - Manifest creation date and time
  - Departure time (if applicable)
- Personnel Information:
  - Name and signature of the postal worker preparing the manifest

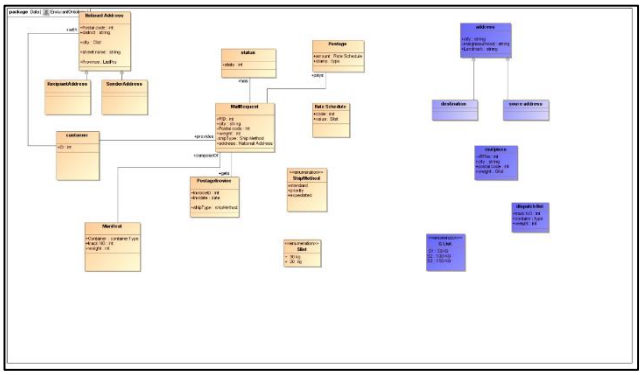

Fig. 5. Postal system endurant domain ontology.

## VII. GAPS DETECTION

The gap analysis aims to discover the alignment of new business processes with business objectives and how far the current practiced business process is from this newly adopted one (which involves some change). The software packages, with their new embedded business processes, define new practices and standards (stemming from research and long experience of Gaint enterprises) for a given domain of business, such as accounting, purchasing, recruitment, etc. It turns out that the identification of noncompliance and its processing is a complete process following the principles of quality management [26].

This section aims to build on the principles established so far to standardize and formalize the gap analysis process that establishes the base for automation.

It is obvious that now we need to focus on P-act/ c-facts; that would be the starting point in observing the differences even between two BPs from different domains. ERP or other Enterprise packages is to replace a business process from the same business domain. For instance, an accounting business process is expected to replace another accounting business process but not purchasing, for example. However, how do we know if two P-acts have identical matches or semi-matching?

Colomb [22] argues that P-act is the stable result which means the c-acts are variable part. Therefore, the difference arises in the set of C-acts with their C-facts that realize the stable result P-act. The assumption supported by principle B; says two c-facts are identical because they belong to the same class or type based on a unified ontology that specifies the vocabulary being used and provides standard meaning. However, the kinds of P-facts and C- facts and how their creation is performed will

ultimately make the fundamental difference. This suggests that we need to do a deep analysis of C-acts. So, the fundamental question becomes when and how two corresponding C-acts are different. The domain ontology reduces this problem into a matching function that asserts where an individual (c-fact) belongs to some existing class. Furthermore, this mechanism can be extended to implement like the Substitution principle that makes whenever an instance of the superclass is valid, the instance of the subclass is valid [27]. Therefore, a superclass with a stronger postcondition can substitute a subclass with a weaker precondition.

This work argues that the practical consequence of this approach is that the production of the same facts signifies the same behavior assuming the same domain.

However, given two similar P-facts, there might be some functional or non-functional (the fundamental assumption of change, such as adding efficiency or economy to business process) differences, but that must be reflected in the C-acts with their C-facts in some way, such as extra inputs or/and different sequence of performance of c-acts. Based on DEMO view when two processes or P-acts have identical production facts, they have already make a response to the same first request in O-phase but probably with some different executions commitment , eventually they will be having an exact result stated in R-phase. In principle, these reports a similar behavior, although they may have different scenarios of execution in E-Phase.

### *A. Mapping UML Activity into Ontology Individuals*

The UML activity model [23] represents the business process at a high business level. We need to map it into ontology representation using one ontology representation language in order to make the reasoning. UML activity diagrams represent both static structures, such as action inputs and outputs, and dynamic processes. From an ontological perspective, for each endurant entity, represented by a class model, there exists a perdurant entity that brings it into existence. This implies that data and processes should be consistent, with each data element resulting from a specific action. We utilize activity models to represent these perdurant entities. Crucially, the domain ontology metamodel (Principle B) serves as the primary source of these facts. They are the set of related P-facts and C-facts of the organization worlds: P-World and C-world. We can do this mapping as definitive statements in OWL( or any other ontology languages ), such as asserting that there is an individual P-fact, visa reference number in Fig. 3 process : P-act(visa- No, date) or asserting fact such as an invoice: C-fact(invoice-No, date, amount). These facts are usually augmented with the specification of transactions in the process model, getting a visa, for example.

The output of this mapping process is a set of facts (as will be shown in the case study) of metamodel level 1 because it models objects that are instances of metamodel level 2 [14]. From OWL prospective, a c-fact is an individual that does not belong to any class but has a set of properties. The properties of the individual are kind of Datatype property. Concrete objects, or specific instances, such as a visa application for Mr. David, are considered level zero individuals. A concept fact (c-fact) can be defined by a combination of properties with literal ranges. For example, in the case study presented in Fig. 6, a mailpiece, produced during the E-phase of the postal system's main mail delivery process, is a c-fact. This mailpiece represents an essential communication document (c-act) for delivering packages, letters, and other items. Properties of this individual c-fact, such as the sender's address, have a domain of 'Customer' and a range of a literal (e.g., string). Similarly, properties like city, state, and zipcode are also literals. Other properties, such as stamp and postage amount, have numeric ranges. Conversely, meter info is likely an object property with a range that is a class with a defined structure. The container type property of the Manifest follows a similar pattern. Because OWL allows the representation of meta-levels [23] within a single model, unlike UML, OWL and RDFS are commonly used for ontology representations.

The problem of converting UML models into OWL has been explored extensively, yielding results across various methods: MDA (Model-Driven Architecture), ontology profile-based approaches, and hybrid techniques. The choice is about cost-benefit analysis approach which has been elaborated with concrete examples by a fruitful OMG ODM project [28], for sake of simplicity will not be considered here.

The view of processes is needed because it consumes the Endurant facts which is a sequence of c-acts corresponding to a specific P-fact. Because OWL does not directly recognize P-acts and their related c-acts, the workaround is to add a meta property, called 'type,' for each act to classify it into one of a set that can be constrainted to c-act,p-act,c-fact,and p-fact . In fact, all c-acts and P-acts can be modeled as OWL classes that can have a set of OWL or RDF properties. Alternatively, OWL-S can be used since it supports service modeling, such as atomic and composite services. OWL-S has a rich structure capable of modeling inputs and outputs. However, we use OWL for its simplicity and comonality.

Fig. 6 illustrates a business process involving concept acts (c-acts). To produce the manifest (main perdurant fact, or p-fact) through the ontological action 'generate manifest,' a mail item is received by the action 'receive mail.' Note that some actions, such as the first two in process A, are manual steps. Consequently, a sequence of concept acts (c-acts) must be executed.A mail package will be gauged,, then a formal request will be created, create request, a service fee will be calculated by calc service fee, and sorting of packages will be thorough Sorting action. These c-acts have a sequence (incoming edge and outgoing edge), input(s) and output sometimes. However, process B in the right side of Fig. 6 is similar to that but involves some differences (discussed later in details) which represent the to-be system or target.

To specify a general method of mapping acts in Activity model to OWL, we can make some abstraction. We do model a property called next for keeping track of the sequence in c-act individual.

### *B. Mapping Target Ontology Into Source Institutional Facts (Principle C)*

The domain ontology is all about intuitional facts. These institutional facts as discussed are created by speech acts under some context which represents framing rule. However, the situation now is we have got two different worlds of institutions:

to-be system and as-system so the question how do we know the institutional facts of to-be system is similar or matching the as-system's institutional facts which as argued in this research as fundamental principle. This distills down into finding a base where the automation machinery going to present later can use it to decide such as on the gap between source and target. Consequently, this step is essential for the following stages, which is about mapping and comparing processes. This aim to establish correspondences between the c-facts from the two different worlds; will refer to them to-be system as the target world, based on intuition that we need to move towards the new system and as-is system will be called the source world, based on the perspective of the main production act.

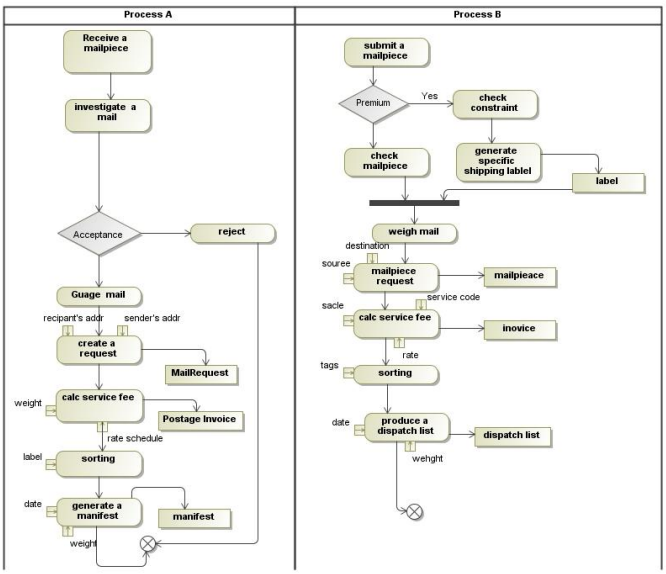


Fig. 6. Postal system main business process (Perdurant ontology.)

How far or near the target from source is the principle of ontological commitment (re-use) which can be low or high as dicussed. The commitment will be low when an ontology used in its usual scope. However, the inputs to the mapping process consist of the two ontology worlds, along with the documentation of the target world (e.g., data dictionaries and BPMN models) .The output is a specification of alignments, mapping target institutional facts to source institutional facts, which depends on the level of ontological commitment. In extreme cases, this may result in extending the ontology with new concepts or creating specializations (subclasses).

More importantly, as demonstrated in the case study, generating the manifest—the main production act—requires a set of C-acts to be performed. These acts lead to the fulfillment of a commitment or promise to create a mailpiece. A mailpiece consists of several attributes: sender, recipient, stamp, and postage amount. This perspective provides a conceptual link that helps track or connect these elements.

A domain expert may observe a similar structure for the mailpiece, though with some variations—for example, differences in naming (e.g., "service amount" instead of "postage," or "meter info" instead of "stamp") or the presence of new concepts not originally defined in the system (e.g., "date," "log info," etc.). These variations are often captured in a data dictionary, which defines the business vocabulary. While precise terminology is ideal, a degree of flexibility is acceptable at this stage, with a greater focus placed on identifying key roles and entities.

Business analysts typically consult both the data dictionary and documentation of the business process—such as BPMN diagrams or activity models—when performing alignment activities. This approach is a common and effective practice within enterprises, as it allows experts to focus on the primary roles and major institutional facts, which serve as abstractions for complex systems. In principle, this alignment process can be automated or semi-automated as in the literature.

It is common for business analysts or ontology engineers to identify relationships or mappings between concepts, whether at the schema level or instance level. This challenge is well-known in the literature and is often referred to as semantic matching, semantic mapping, or ontology merging [29]. Several approaches have been developed to identify relationships such as equivalence, subsumption, and others. Tools like LogMap [30] and the Alignment API [31] are widely used for this purpose. According to this activity untimely will end up with a table similar to Table I (based on the case study) in which the target concepts mapped into their corresponding source c-facts P-facts. The ontology can be built either based on source world or target world since mapping has been performed.

TABLE I. MAPPING TARGET INSTITUTIONAL FACTS INTO SOURCE INSTITUTIONAL FACTS

| Source | Target | Comments |
|---|---|---|
| Mail request | Mailpiece | Similar |
| manifest | Mail list | Some differences more attributes added |
| Invoice | Invoice | Similar |
| Guagement | weights | Different scales |
| | | |

### C. Generating Implication Rules Based on Corresponding Actions(D)

We have now a unified ontology has been annotated with the target concepts after mapping as explained in the previous section. This section will deal with the base for matching and discovering the gap between two business processes.

As Colomb [22] argued, the stable result is the production act, meaning that all different c-acts and their associated c-facts will not change the reality of p-fact. Additionally, an institutional fact can be understood as a record of a speech act. Furthermore, as stated in the quote, “the state of the P-world at a specific point in time is defined by the set of P-facts created up to that moment, while the state of the C-world at a specific point in time is defined by the set of C-facts created up to that moment.” In simpler terms, the creation of a fact of a particular type represents a state transition within one .of these two worlds.

This implies that we can trace the primary production acts by examining the pre-c-facts generated during the E-phase and the post-c-facts generated during the R-phase. Consequently,

when two distinct c-acts result in the same c-fact instances, it indicates that they exhibit similar behavior.

Therefore one can observe that dependencies usually exist in the creation of c-facts, which often follow a logical sequence. Fig. 7 illustrates that the main production fact, the Manifest, requires the creation of two necessary c-facts: Mailpiece (c-fact1) and Invoice (c-fact2). Additionally, each c-fact can be associated with a set of c-acts that were performed prior to its creation (referred to as the c-world state), which contribute to its existence. This observation suggests that we can use these facts as a basis for tracing and matching subordinate elements between two worlds.

For instance, both Mailpiece and Manifest have sets of c-acts that contribute to their existence. Let us refer to these sets as Set M (for Mailpiece) and Set F (for Manifest). In this context, Set F is a proper set, while Set M is a subset because the Manifest encompasses multiple Mailpieces. This implies that the Manifest represents the whole, while the Mailpiece is a part of that whole. Consequently, there may be many parts (Mailpieces) that belong to the same whole (Manifest). Therefore, in this case, we need to identify the corresponding whole in the to-be world and construct similar sets of c-acts.

Since institutional facts from the to-be world are already mapped to corresponding institutional facts in the as-is world (principle c), it is possible to define a mapping function or make a relationship between them (i.e., they contribute to the creation of the same fact). Once these sets are constructed, a more specific matching between corresponding sets of c-acts can be established. For example, in Fig. 7, the Mailpiece has its corresponding MailRequest, and actions such as Gauge Mail and Weigh Mail are also corresponding actions.

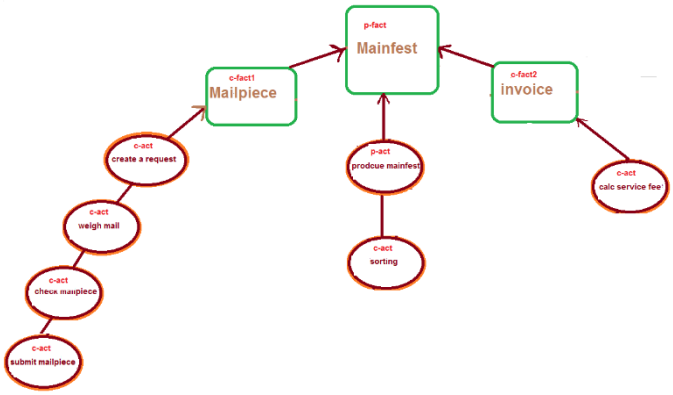


Fig. 7. Example of dependences among c-acts that contribute to the Production fact Mainfest.

More importantly, I argue that, based on this perspective, we can conceptualize an implication rule where the left side (a set of c-acts from Process A) implies the right side (a set of c-acts from Process B), provided that the major institutional facts (i.e., c-facts) are similar.

Furthermore, we can closely examine the direct relationship between the left-side and right-side sets by analyzing the inputs to c-acts and matching them with the standard domain ontology through querying or assertion. This process ensures that all inputs originate from the same ontology. In this context, we will have a set of properties derived from different classes. These classes belong to the left-side and right-side sets, which are either similar or represent different versions of the same entity—the institutional fact.

Now our ultimate goal is to determine when a BPs fail to be replaced by other BPs. The failure is because of different reasons but we argue that it can be commonly studied under incompatible classes or individuals in which properties are conflicting. Therefore, we need to look at the specific problem of when two classes are incompatible because at least one property in first class conflicts with the corresponding class's property. Hence a reporting of mapping failure with evidences. However, identifying these discrepancies is essential where a business can leverage them to adopt potential and necessary change (gap analysis principles).

Now let us take concrete feedback from our case study, Fig. 7 models part of a main business process in postal system that have the original BPs or as-is system, call it Process A and the to-be system, call it process B.

Process A:

*1)* Recive a mail
*2)* Check mail
*3)* Decide Acceptance - input – mailpiece info
*4)* If accepted then
*5)* Guage mail - input : mailpiece output : weight
*6)* Create mail request : output mailpiece request
*7)* Calcuate service fee
*8)* Make invoice : output invoice
*9)* Sort mailpieces
*10)* Generate manifest : output manifest

Process B:

It is similar to A but it has additional subprocess premium service that is not considered by A. Assume for simplicity the following differences.

*1)* Recive a mail
*2)* Check mail
*3)* Decide Acceptance - input – mailpiece info
*4)* If accepted then
*5)* Guage mail - input : mailpiece output : weight
*6)* Create mail request : output mailpiece request
*7)* Calcuate service fee
*8)* Make invoice : output invoice
*9)* Sort mailpieces
*10)* Generate manifest : output manifest

From step 2, for example we have a subprocess running in parallel to deal with premium service:

*1)* If premium service then
*2)* Check constraints
*3)* Calculate service fee
*4)* Confirm payment : output receipt
*5)* Generate shipping label : Output new label
*6)* Priortize handling : output special manifest

Let us imagine also three major differences in institutional facts between A and B described by Fig. 6, blue classes at right side): National address (NAaddress) that is introduced as a new government regulation in Process B. It follows a different format, including fields such as landmark, city, and neighborhood, postage amount is specified in the local currency, measurement units (guagment): There is a difference in measurement systems; Process B uses local weight standards with a different scale.

These cases can be summarized in the following (Process A):

*1)* In mailpiece the type of postage amount is Rayal currency.

*2)* Also in mailpiece as well as mainfest the addresses are formed from the structure of { a-building No (4-digits),b-street name (15-character), c-district(limited set of values : all local district for a city),city (limited set of values: all local country cities), etc}.

*3)* Guagement is a set of 50 kg, 100kg, 150kg, etc.

A prior knowledge is that the to-be system or process B has US dollar currency in any financial transaction also does not support the national address's structure and 15kg, 30 kg weights scale (i.e. large volume of business is in this scale) because the to-be system has only Mutiple of 50kg.The data dictionary of these systems could be a good source for investing such requirements or information.

It is required now to generate the implication according to the principle of finding the corresponding of institutional facts. Since we already have the specification for business processes as part of ontology in an ontology language like OWL (as described in …), this step is going to extend that to incorporate this implication generation step. The mapping of institutional facts in the source to target institutional facts will act as an input to this process (i.e. Table I). It can start with finding the main production fact and their subordinates or c-facts. Then mapping this main production fact to its corresponding fact from source.

In the case study the main manifest and manifest are similar concepts and represent the same real-world entity. Having different names or synonyms for the same concept can be automated as in the literature using corpus or wordnet and dictionaries methods [32]. It can classify concepts into the same class when they are belonging to these relationships: is-kind-of or is-a (always hold) and part- of a whole.

*1) Main production fact rule*

1. Mainfest $\longrightarrow$ postage invoice, mail request

2. Main Maninfest $\longrightarrow$ inovice, mailpiece, label

Based on Table I and the principle of left side implies right side then it follows that:

postage invoice, mail request $\longrightarrow$ novice, mailpiece, label

Also from Table I:

*2) Branching*

1.1 Post invoice $\longrightarrow$ invoice

1.2 Mail request $\longrightarrow$ mailpiece

1.3 Since label has no corresponding concept in table 1 it means new entity needs to be added to the ontology of new business process world. There are two interpretations in this case a) new requirement does not exist in the source so far b)or more refinement for existing concept(s).

Then we need to find out what are the speech acts (c-acts) have contributed to the production of these c-facts from both side of implication which will inherit this implication also.

*3)* Based on B will get the following implication of acts as consequence :

For 1.1:

calc service fee $\longrightarrow$ calc service fee

Also,

For 1.2: create request $\longrightarrow$ mailpiece request

Therefore, we conclude that the inputs to these c-acts are also equivalent

Weight, rate schedule $\longrightarrow$ scale, rate

By querying or asserting the developed ontology in principle B) above we will discover that they are not different concepts.

Make a request $\longrightarrow$ Create a request

Sender, Receiver $\longrightarrow$ source, destination

We need now to identify their corresponding classes in order to discover their incompatibility and properties in conflict. Since OWL and SPRQL has standard ontology to represent properties with its different rich characteristic functions, we can develop standard methods.

To identify incompatible classes, we can approximate the problem using the concept of subsumption. In mathematics, we say that class A subsumes class B if every element of B is also an element of A. In other words, B is contained within A, and we can say that A represents B. One can think of the relationship between the to-be system and the as-is system using the substitution principle: if A is a superclass of subclass B, then an instance of A can substitute an instance of B. However, we need to investigate the conditions under which this substitution is valid or invalid. If we can determine that business process A (the to-be process) subsumes business process B (the as-is process), then we might conclude that A can replace B. To reach such a conclusion, a set of operations—such as intersection, set difference, and others—must be applied.

But how do we know when substitution is not possible? For example, in the case of a more constrained subclass, substitution may break. According to set theory, if two sets differ in their elements—either by having disjoint elements or partial overlap

with at least one exclusive element—then they are not equivalent.

However, in this context, we need more precision. We require a rigorous definition of what it means for an element to be "different." One way to realize this is by examining conflicting properties. These conflicts help determine incompatibility. Therefore, we address this question in the following section.

There are of course many reasons for discrepancies that are difficult to count but it can be generalized under common classification theme such as in Table II, then for each class we provide a treatment.

TABLE II. AN EXAMPLE OF DISCREPANCIES AMONG PROPERTIES BASED ON THE CASE STUDY

| S | Concept in A | Type | Is_essential? | Concept in B | Type | Difference |
|---|---|---|---|---|---|---|
| 1 | amount | Property | No | Postage amount | property | naming |
| 2 | NA address | Set of Properties for a class | Yes | address | class with different set of properties but it has some common items | Structure |
| 3 | gaugement | Set of individuals for a property | Yes | wight | properties | Range – different scale |
| 4 | tracking | class | NO | New class with properties | Does not exist | Not esists (to Model new class object) |

Table II demonstrates the concept in process A (source) and the corresponding concept in process B (target), type of concept from ontology prospective (class, property, etc.) with their differences stated. Moreover, a column is added to adopt metaproperty is_essential that discriminates or defines the essential properties for each class. An essential property is one that must exist in each instance. This can be based on the theory of BWW (Bob). The purpose of proposing it here is that the final decision of dissimilarity can rely on it which allows this task to be automated.

### *D. Building Standard Queries and Assertions (Principle E)*

In order to reason about discrepancies, we need to standardize and formalize testing of a gap in the form of assertions and quires. The basic assumption is to use SPRQL since we ended up with ontology specified using RDF-based language (OWL). An alternative is use the built-in machinery of consistency check [33] but there is no more control especially if customised quires or assertion are required.

Referring to Table II, one can infer that some properties have been converted into class types, such as the NA address in the new process (No 2). Additionally, the range of one property has changed, resulting in a subsumption relationship, as seen with 'gaugement' and whight; the initial range is a subset of the new range, indicating a change in the property range's scale. Furthermore, a new property has been introduced in the new system, which was absent in the legacy system, as illustrated in case 4(tracking).Therefore, the following queries demonstrate how to reason about these cases based on the source and target ontologies given.

*1) Range discrepancy query:* This is typically for like case 3 in Table II. The first obvious case occurs when the value of a property in target class does not belong to the range class of the source(i.e. range of source is mailpiece while the range class of target is manifest).Second, the range of the source property is more specific than the target property( target range for instance is a set of red and yellow while source is bule only).

The discovery of the first case is straightforward because we can use the SPRQL not exist in the filter clause to assert that an individual has property's range of the source (i.e. postage amount is not riyal). The second case can be obtained by different ways; one way is to use OneOf OWL construct that allows to specify, for example, a property having specific range (enumeration data type).Therefore, we can use SPRQL to disprove that the range set of the source is not either subset or proper set of the target. For instance, the base to discover the incompatibility in case 3 in the Table II:

```
# Check subset condition, A ⊆ B: every member of Set A is also in Set B
Select? x
FILTER NOT EXISTS {
?x rdf:type :RangeOfClassA.
FILTER NOT EXISTS {?x rdf:type :RangeOFClassB }
}
```

The Not-exists clause will return false always except when one tuple appears in the result showing that one member of set A is not part of set B.

```
# Check proper subset condition, B ⊇ A: there exists a member in Set B not in Set A
FILTER EXISTS {
?x rdf:type : RangeClassB .
FILTER NOT EXISTS {?x rdf:type : RangeClassB }
}
}
```

Notice that this is the inverse of the first query so the Not-exists clause returns true only when there is a member in B does not belong to A.

*2) Structure discrepancies query:* It is typically like case No 2 in the table where a property needs to be replaced by a class(NA address ) which is a recurring problem. Since based on DEMO their corresponding classes are from the same P-act then some overlapping of properties might occurs. However, there are different types of structure differences that might happen. Mostly these will recur in the whole ontology and the

advantage of this is that a bench of quires will be re-used, therefore reducing the cost of the development. In the following these different types of structure discrepancies will be sketched.

Type1: Class range vs. property range

The following query will return instances of properties that at most one of its range is a class. The postage amount in target could ranges over specific class (standard list) while the source amount has range integer.

```
SELECT ?Property1 ? Property2
WHERE {
 ?property1 rdfs:range ?range1 .
 ? Prpoerty2 rdfs:range ? range2
 FILTER NOT EXISTS (( range1? Owl:datatype ?) And (range2 owl:Class })
 }
}
```

Type 2: Ranges are classes but one subsumes the other

Using proper set and subset check as discussed above allows us to make a test for which is a subset of another, but before that an initial test is required to map corresponding properties instead of comparing a source property with all target properties. For example, Address and NA Address, in such a situation Hamming distance can be used which computes distance between two strings. Properties can be encoded using bitmaps such as 4bits for each character (we need determine the size based on the dynamic range of characters exist). The Hamming distance function computes how many number of characters are in differences. In this case, it will result in less distance between NA address and Address than among other properties. Also, the case could be two different names of properties used but with the same semantic meaning. For example dispatch list and manifest .A well-established method of Wordnet [32] can classify these concepts into the same class which is an is-kind relationship. Wordnet-based methods can also detect is and part-of relationships.

Type 3: Cardinality discrepancies

More restriction could be specified on ontology of source and target where properties have specific cardinalities (min, max) therefore must present in testing. For example:

- A Manifest must include at least one Mailpiece (a manifest cannot be empty).
- A Mailpiece can be included in at most one Manifest (a mailpiece cannot be listed on multiple manifests).

Min/Max cardinality test: Remember this test on TBox or the terminoglical level of the ontology but not instance level.Therefore we need to teat ComposeOf property if it specifies max or min cardinality .Usually OWL allows one to make these constrains by defining a subclass of the restriction class (OWL built in).In the following a query ComposeOf for this case will be checked for if it has min cardinality constraint. Constraint and card value are variables will be instintiated when the where condition satisfied. The where condition binds a restriction variable with instance if it finds rdf type owl:Resitirction class which has property ComposeOf.

```
SELECT ?constraint ?cardValue
WHERE {
 ?restriction rfd:type owl:Restriction ;
 owl:onProperty : ComposeOf;
 ?constraint ? cardValue .

 FILTER (?constraint =minCardinality)
}
```

Based on that queries and assertions we will be able to verify if any major differences exist for essential properties of the source ontology and accordingly, we can reach to the final decision of compatibility or not because of the exitance or not existence of conflicting essential properties.

We could combine or package these quires to be executed in a sequence using Nested substructure where select ... is going to be nested or chained. Therefore, we can get one final and single answer for a couple of quires and assertions. Moreover, the implication rule principle can be automated and linked with this these queries using XSLT which can transform the implication rule into a direct call to APIs that will perform the necessary tests as explained above.

TABLE III. COMPASSION AMONG THE METHODS USED FOR GAP ANALYSIS

| Criteria | Manual inspection | Process Mining | Proposed method |
|---|---|---|---|
| Automation support | No | Yes | Yes |
| Semantic heterogeneity | Yes | Yes | No |
| BP Instances required | No | Yes | No |
| Error rate | High | low | low |
| Reliability | Low | High | High |
| Performance | Low | High | High |
| Scalability | No | Yes | Yes |

## VIII. DISCUSSION AND INTERPRETATIONS

Enterprises often adopt new and innovative business processes under the assumption that they will lead to breakthrough results. However, if such changes are implemented without sufficient preliminary analysis, the risk of failure significantly increases. For example, a recently established company in the region specializing in paper manufacturing and recycling—with a capital exceeding one million dollars—faced failure during an attempt to upgrade its systems and reengineer its business processes.

Traditional approaches in such cases are typically ad hoc, suffer from semantic heterogeneity, and lack scalability due to inherent complexity. Table III shows a theoretical comparison based on expert reasoning of manual inspection, process mining, and the proposed method across several key criteria: semantic heterogeneity, instances requirement, automation support,

errors, reliability and scalability. As demonstrated, manual inspection is unreliable, has a high error rate, and lacks automated support. Although process mining increases automation and reliability, it does not address semantic heterogeneity and is still dependent on the availability of process instances. By removing semantic heterogeneity and lowering reliance on process execution logs, the suggested approach outperforms both process mining and other methods while maintaining high reliability and performance. This comparison serves to highlight the anticipated benefits of the suggested approach, even though empirical validation is still a future objective.

Since business processes (BPs) are fundamentally about institutional facts (i.e., production facts), the model proposed in this article offers a way to mitigate such risks. It does so by unifying the institutional vocabulary used by businesses to describe their expected services and products.

This unified vocabulary enables standardized gap analysis, supported by DEMO, which provides a formal language for expressing the essential elements of a business process—abstracted from implementation and realization details. Such abstraction is a powerful tool for managing complexity.

Furthermore, comparing the ontologies of to-be and as-is business processes is feasible because both originate from the same business domain. Various scenarios can arise, such as one process being more constrained than the other. These discrepancies can often be grouped under common classes, allowing the development of a general method for systematic analysis and resolution.

One related outcome of this work is that it facilitates documenting gaps so they can be understood at a high level, as argued by Jeston [34]. This is the fact that models are transformed into a knowledge-based system; therefore, it not only supports reasoning about gap but also acts as an informative repository that can be reused for different analysis goals, which is a principle aligned with the BPM objectives. For example, top managers, executives, and strategist are interested in answering inquiries about different business processes for various reasons, such as benchmarks to determine enhancements for as-is processes that can justify the investment [35].

The major cost is developing an ontology manually for a domain of business processes or institutional facts. Also annotating the model with DEMO concepts and mapping target institutional facts into source institutional facts. However, some capabilities of the ontology toolset can be utilized to some extent, such as ontology learning, consistency check and the model's mappings facility of QVT to reduce this cost. Moreover, conducting large-scale evaluations in different domains with different scenarios will highlight more classes of discrepancies. These are elements of future work.

Regarding the reengineering process itself, standardization enabled by DEMO helps to define the kind and type of change required as usual practices of adopting new ERP (commits to ERP ontology). Therefore, the problem would shift to focusing on which institutional facts (C-fact and P-fact) need to be changed as well as its set of actions (C-act and P-acts). Moreover, DEMO provides an ontology to talk about processes gap and their classification.

## IX. Conclusion

This study examines the challenges of gap analysis problem when replacing legacy business process (as-is) with new business process (to-be). Business processes evolve to incorporate qualities such as economy, productivity, and efficiency, necessitating a thorough analysis to ensure alignment with organizational objectives and strategy. Gap analysis plays a critical role in answering key questions, such as whether a new process can replace an existing one and, if not, identifying the reasons. This work proposed a structured method to identify gaps among business processes. It consists of Four principles: 1) Developing DEMO profile (principle A) 2) Building domain ontology for BPs (principle B) 3) Mapping target institutional facts into source ontology (principle c) 4) Generating Implication rules based on corresponding actions 5) Reasoning using standard discrepancy quires(principle E). Because business processes are about the production of institutional facts, semantic heterogeneity prohibits comparing and analyzing two different processes ( main source of failure); building domain ontology(consists of both endurant and perdurant) that unifies terms, concepts, messages and interpretation is an essential process in the proposed approach (principle B). This suggests mapping the to-be system's institutional facts into their corresponding source's institutional facts (principle c). Also, DEMO has richer concepts for designing business processes that focus on the Essential model of an enterprise. It handles the complexity through the identification of the main production act, p-act, which is the stable result. Therefore, a set of c-acts could be identified and compared that is required for the existence of the P-fact (i.e. manifest) b; business activities independent of realization and implementation issues. Therefore, a UML Activity as a famous design language has been profiled to support DEMO concepts (profile A). Integrating DEMO concepts into UML activity Diagram puts forwards and facilitates the analytics of business processes. This suggests that we reason about gaps using such as SPRQL (Principle E). However, this study contributes to the state-of-the-art of BPM and ERP community by providing a facility to compare different business processes semantically, either as legacy or new processes, providing a great opportunity for business analysts, architects, and strategists to make critical (multi-million dollars) decisions.

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# Investigation of Convolutional Neural Network Model for Vehicle Classification in Smart City

Ahsiah Ismail[1], Amelia Ritahani Ismail[2], Nur Azri Shaharuddin[3], Asmarani Ahmad Puzi[4], Suryanti Awang[5]
Department of Computer Science-Kulliyyah of Information and Communication Technology,
International Islamic University Malaysia (IIUM), 53100 Kuala Lumpur, Malaysia[1, 2, 3, 4]
Faculty of Computing, Universiti Malaysia Pahang Al-Sultan Abdullah, 26600 Pekan, Pahang, Malaysia[5]

***Abstract*—Smart city optimize efficiency by integrating advanced digital technologies, real-time data analytics, and intelligent automation. With the evolution of big data, smart cities enhance infrastructure and provide intelligent solutions for transportation with the integration of high-level adaptability of computer technologies including artificial intelligence (AI). The optimization can be achieved through predictive analytics in providing intelligent solutions for transportation. However, this requires reliable and accurate informative data as input for predictive analytics. Therefore, in this paper, five models of Convolutional Neural Network (CNN) deep learning method are investigated to determine the most accurate model for classification; namely Single Shot Detector (SSD) Resnet50, SSD Resnet152, SSD MobileNet, You Only Look Once (YOLO) YOLOv5 and YOLOv8. A total of 1324 vehicle images are collected to test these CNN models. The images consist of five different categories of vehicles, which are ambulance, car, motorcycle, bus and truck. The performances of all the models are compared. From the evaluation, the model YOLOv8 attained 0.956 of precision, 0.968 of recall and 0.968 of F1 score and outperformed the others. In terms of computational time, YOLOv5 is the fastest. However, a minimal computational time difference is observed between the YOLOv5 and YOLOv8, which were separated by only 20 minutes.**

***Keywords*—Vehicle classification; Convolutional Neural Network; SSD; YOLO; MobileNets**

## I. Introduction

"Smart City" is a city that utilises technologies, data and digital solutions to improve the efficiency by equipping systems and services with additional cameras and sensors to collect data [1]. Then it integrates with various services such as transportation networks, public transit, utilities, and others to improve its operation and the quality of life. In a smart city, the huge volume of data collected using vision sensors can be used to improve services provided by the city, especially for the road traffic management system. Monitoring the road monitor traffic congestion is important as the number of vehicles continues to increase every year. Starting from 2021, over 71 million vehicles are sold globally [2]. This shows that there is a need for efficient traffic monitoring and management systems to avoid traffic congestion.

With the increasing number and volume of traffic data vehicles on the road, effective road traffic monitoring is crucial to improve the flow of traffic, minimizing accidents, and reducing traffic congestion [3]. Vehicle classification plays an essential role in optimizing the road traffic flow and enhancing road safety. Different vehicle types, such as cars, buses, trucks, and motorcycles, have distinct speed, space, and acceleration characteristics, affecting congestion patterns. Accurate classification helps in traffic signal control, lane management, and smart tolling systems to ease the congestion. Thus, this will also allow predictive solutions and decision making for better road planning and road traffic management system. With the integration of Artificial Intelligence (AI) for road traffic monitoring, traffic congestion may be reduced by offering a predictive solution for future planning and decision making. The predictive analytics in AI can predict congestion by using historical data, detect accidents and related events in a short time, and optimise public transportation schedules, which will reduce the occurrence of congestion. In delivering a high-quality predictive solution for future road traffic monitoring, a highly accurate method is needed as reliable and accurate information for effective traffic management. Therefore, in this paper, we investigate the reliability of artificial intelligence using Convolution Neural Network (CNN) of deep learning models to classify between types of vehicles for road traffic monitoring. The types of vehicles on the road, information and vehicle distribution can be further used as the input for analytics model for future prediction of road traffic conditions. The analytics synthesize, analyze the trends and identify the patterns based on the data for future planning, decision making and actions to improve the road traffic monitoring.

This research focuses on the detection of a suitable CNN deep learning model for vehicle classification. The CNN method is chosen since it is one of the most reliable deep learning models which can automatically extract meaningful patterns and features. CNN utilizes its convolutional and pooling layer to preserve spatial relationships within an image which allows it to recognize objects regardless of its position in an image. CNN uses shared weight through convolutional filters which may reduce the number of parameters compared to a fully connected network. This capability will reduce the time complexity as fewer computations are needed, making CNN method a fast-training method [3].

To test the proposed CNN model, datasets of vehicles that consist of 1324 vehicle images from five different categories of vehicles which are ambulance, bus car, motorcycle and truck are created. Then, the performances of the CNN models are compared between Single Shot Detector (SSD) Resnet50, SSD Resnet152, SSD MobileNet, You Only Look Once (YOLO) YOLOv5 and YOLOv8 in terms of precision, recall, F1 score and computational time. The rest of this paper is organized as

follows: Section II presents the related work on the vehicle classification methods. Section III described the details of the proposed method. Section IV presents the experiment setup. The performance of the proposed method is presented in section V, followed by the discussion in Section VI. Finally, the conclusions and future work are highlighted in Section VII.

## II. Related Work

The accurate prediction of road traffic patterns and vehicle types able to improve road traffic management. Early detection of traffic congestion and vehicle distribution is essential for prediction of road traffic conditions, optimizing traffic flow, and enhancing future planning for road transportation. Object detection methods play a crucial role in identifying and classifying the objects in images [4]. With computer vision technology and deep learning object recognition methods, smart traffic systems able to offer the automated detection and classification of various types of vehicles on the road. This enables more efficient traffic control monitoring. However, in vehicle detection and classification, achieving an accurate classification and consequently prediction remains a challenge due to factors such as varying lighting conditions, occlusions, and diverse vehicle appearances [5, 6].

In recent years, the deep learning-based models show the best performance in detecting objects with high classification accuracy [7]. In the intelligent transportation system, deep learning models able to automatically extract important features in order to classify vehicles such as motorcycles, buses, cars, ambulance and trucks into their own category. This will enhance transportation systems, especially road traffic monitoring and road safety to reduce traffic congestion. The deep learning methods focus on the useful features which are extracted automatically. The methods analyse extracted features with similar logical structures as the human brain which enable to obtain more accurate results compared to the other methods such as statistical, morphology and model-based methods. The deep learning method, able to improve object detection and classification [8].

In deep learning, the CNN method is the most promising method that is able to effectively extract the significant features of the object and able to achieve high classification accuracy in most of the application [9] . In CNN method, there are the two object detection which have gained popularity, namely Single Shot Detector (SSD) and You Only Look Once (YOLO). These methods have gained popularity due to their accuracy performance [10].

The SSD is an object detection framework which predicts a bounding box in a single forward pass through a deep neural network. To perform detection on objects of various sizes, it uses multiple feature maps at different scales. SSD have gained popularity as they balance well between speed and accuracy. SSD combined with different types of ResNet architecture will result in different SSD ResNet models such as SSDResNet50, SSD ResNet152 and SSDMobileNet. SSD ResNet50, combines SSD with ResNet-50 as the backbone, which is a deep convolutional neural network consisting of 50 layers. It is suitable for real time applications with moderate computational power. The SSD Resnet152 on the other hand uses a deeper neural network with 152 layers. The increased number of layers in the SSD Resnet152 able to improve the classification accuracy of the model. However, this increases the time complexity. The model that able to reduces the time complexity while maintaining a reasonable amount of accuracy is the SSD MobileNet [11]. The SSD MobileNet model is design and optimized for the mobile.

Apart from the SSD model, YOLO model is also widely used for object detection. It frames object detection in images as a regression problem for separated bounding boxes in YOLO. It also provides an image with captions and the object is highlighted with the probability of correct detection. YOLO models are also seen to be the most suitable model in many detections and classification tasks as it shows promising results and able to obtain high classification accuracy in object detection and classification [7]. There are two advanced versions of YOLO, namely YOLOv5 and YOLOv8. The key differences between these two versions are its architecture. YOLOv5 utilizes anchor-based architecture where the anchor box is needed to be predefined with different size and aspect ratios according to the object used in the image. When predicting, it adjusts the predefined anchor box to better match the actual object. On the other hand, YOLOv8 uses anchor-free architecture which directly predicts the object location by identifying key features from feature maps, rather than relying on an anchor box like YOLOv5.

Due to YOLO are among the most efficient method for object detection, Ghoreyshi et al. proposed vehicle classification based on YOLO of CNN model. In their work, they able to achieve a high classification accuracy with 91% accuracy. This shows that YOLOv3 models have potential in effectively recognizing and classifying vehicles. However, in their research, less detection is observed for the images with occlusion which is a common scenario in real world traffic environments [3].

Similarly, Gao et al. also use YOLO model for the detection of vehicles. However, in their research, the YOLOv5 is selected to classify multi-class vehicle detection. The YOLOv5 models used in their work able to obtain accurate results with 96% accuracy results. The results obtain in their work shows that YOLOv5 methods are effective in real time applications and can be used in traffic monitoring [12].

The performance of YOLOv5 is further explored by Kumar et al. They proposed YOLOv5 with DeepSORT algorithm in their work to address both detection and classification of vehicles in dynamic traffic scenarios. Their research focuses on real-time performance efficiency. The research offers a practical solution in applications which require quick monitoring and decision making in traffic environments [13].

From the above review, SSD and YOLO were among the methods that had been considered in existing vehicle classification. The SSD and YOLO are seen as the most suitable candidate for vehicle classification. Therefore, in this research, a CNN deep learning based method of SSD and YOLO are chosen for vehicle detection and classification. The SSD is chosen due to its ability to balance well between speed and accuracy. On the other hand, the YOLO is selected as it able to obtain high classification accuracy in many object detection and classification tasks. Based on the review, four models which are

YOLOv5, YOLOv8, SSD ResNet50, SSD ResNet152 were among the models that had been considered in existing vehicle classification recognition due to their strength in detection and classification. YOLOv5 shows high accuracy and rapid inference, ideal for real-time applications. YOLOv8 also shows high accuracy and robustness against challenging conditions. The SSD ResNet50 on the other hand able to improve the detection on moderate complex scenarios and better handling the details of the objects than the lightweight. The SSD ResNet152 is also one of the chosen models due to the robust detection in complex traffic scenarios. The SSD is seen to be an efficient model for real-time applications with faster processing speeds [14].

Based on the review, five models which are SSD Resnet50, SSD Resnet152, SSD MobileNet, YOLOv5 and YOLOv8 are seen to be the most suitable model for vehicle classification tasks. The four models which are SSD Resnet50, SSD Resnet152, YOLOv5 and YOLOv8 are selected due to their accuracy and performance in detection and classification. While the SSD MobileNet model is selected due to it ability to reduce the time complexity while maintaining a reasonable amount of accuracy. To determine the best model for vehicle classification in smart city, the performance of these five models namely, SSD Resnet50, SSD Resnet152, SSD MobileNet, YOLOv5 and YOLOv8 are evaluated and compared.

## III. Proposed Model

The proposed model for vehicle classification can be divided into two phases, training and testing. In this paper, generally, two CNN deep learning models are evaluated which are the SSD and YOLO. The overall scheme for the vehicle detection is shown in Fig. 1. Each of these methods will be discussed in the following subsections. To obtain the most suitable model for vehicle classification from these two main models, five different models are tested, and their performance are compared. The five different models are the SSD Resnet50, SSD Resnet152, SSD MobileNet, YOLOv5 and YOLOv8. Each of these models will be discussed in the following subsections.

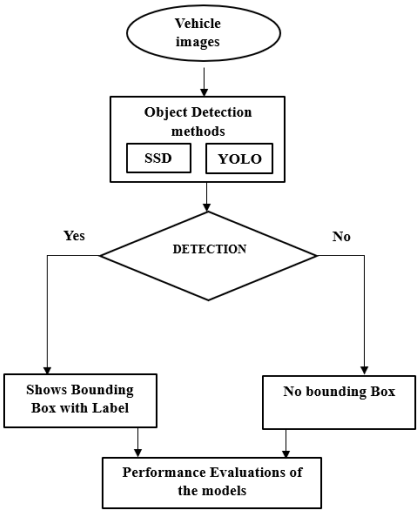



Fig. 1. Overall scheme with two different object detection methods.

### A. Single Shot Detector (SSD)

The SSD is an extension of Convolutional Neural Network (CNN) model architecture which is designed for object detection. The SSD method uses deep CNN for the detection and classification of the object location in an image [15]. SSD utilizes multiple feature maps and anchor boxes to detect objects from various sizes and predicts its location and class score of the objects within the images [16]. Three SSD models evaluated are SSD ResNet50, SSD ResNet152 and SSD MobileNet. The basic SSD architecture is shown in Fig. 2.

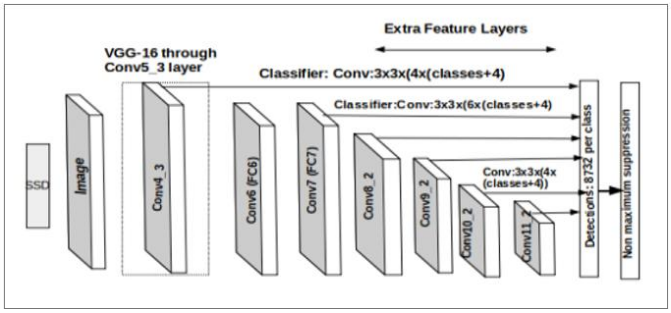



Fig. 2. SSD Architecture [15].

The SSD architecture consists of VGG-16 acts as the backbone of the architecture. The model extracts features from the input image and produces various feature maps which capture different levels of detail in the image. The extra feature layers that include various sizes of layers from bigger to smaller. The feature maps from the VGG-16 produced are then being processed further to create additional feature maps. These additional feature maps are much smaller in spatial size which enables the detection of objects from various sizes. The detection layer feeds on all the feature maps produced by each of the layers and applies a small convolutional filter to predict the class and localization of the objects for each of them. Then, the non-maximum suppression refines the prediction by removing heavily overlapping bounding boxes to finalize the bounding box and class label. To obtain the optimum classification accuracy in this research, three SSD variants are produced by replacing the VGG with three different model namely; ResNet50, ResNet152 and MobileNet. Each of these models will be discussed in the following subsections.

*1) SSD ResNet 50:* The SSD ResNet50 model consists of SSD as a framework with ResNet50 as its backbone. The SSD ResNet50 is an object detection model which has been pretrained with COCO 2017 dataset. This model localizes detected objects by drawing bounding boxes around the object. The model utilizes Feature Pyramid Network (FPN) for multi-level feature maps generation to feed into the SSD framework as the input. During the training phase, momentum optimizer with 0.04 learning rate is used and it is reduced when a plateau in the performance is detected. The SSD ResNet50 model architecture used is shown in Fig. 3.

*2) SSD ResNet-152:* The SSD ResNet-152 model used in this research is the combination SSD architecture with ResNet-152 as its backbone for feature extraction and SoftMax classifier for the class prediction. It is a deep convolutional neural network (DCNN) that consists of 152 layers which

include convolution layers, down sampling layers and fully connected layers. The SSD ResNet-152 model uses deep residual connections to overcome the vanishing gradient issue during the deep network training. The SSD ResNet-152 model architecture is shown in Fig. 4.

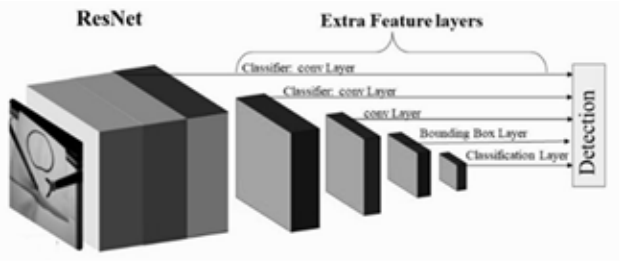



Fig. 3. SSD-ResNet50 [17].

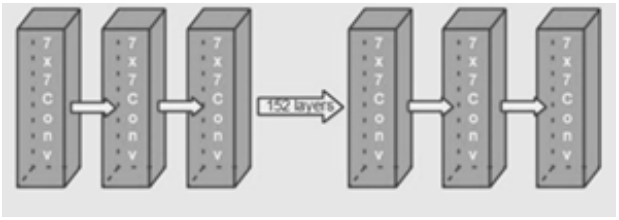



Fig. 4. Architectural diagram of SSD ResNet-152 [18].

*3) SSD-MobileNet:* The SSD-MobileNet is an object detection model which consists of SSD architecture with MobileNet as its backbone. This model is suitable for real time applications as it able to balance between speed and accuracy performance. The SSD-MobileNet is an efficient model where it preserves the important information while processing an image [19]. The model architecture of the SSD-MobileNet is shown in Fig. 5.

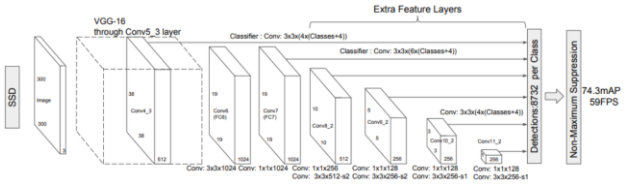



Fig. 5. The architecture of SSD-MobileNet [19].

## B. You Only Look Once (YOLO)

The general structure of YOLO for the classification is shown in Fig. 6. In YOLO architecture, the detection of objects is treated as a regression problem in which the image is divided into grids and the prediction is done by predicting the bounding box and class probability for each grid cell in a single pass, making it exceptionally fast [20, 21]. In YOLO architecture, the vehicle images are resized and standardized to ensure consistency in grid structure and to simplify the process. Then, the images pass through the Convolutional layers which extract basic features of the vehicle images. In the early stage, the convolutional layers are paired with max pooling for down sampling to reduce the spatial dimension of the feature maps produced by the convolutional layer. In this research, the process of reducing the spatial dimension is applied to help the model focus on more abstract features of the vehicle images. This process is repeated several times until it is sufficiently small. In the middle stage, the vehicle images are then pass through a convolutional layer without max pooling. These layers deepen the feature extraction process to capture more detailed patterns. Lastly, the compressed feature maps produced by the previous layers are processed by fully connected layers to output the final prediction in the form of bounding box, confidence score and class probabilities.

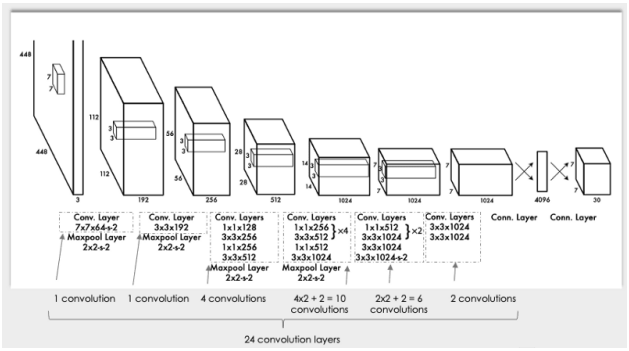



Fig. 6. YOLO Architecture [22].

In this research, there are two YOLO models used for vehicle classification which are YOLOv5 and YOLOv8. These models are chosen due to their speed, accuracy and efficiency in real time object detection. YOLOv5 models are highly accurate with rapid inference time, making it ideal for real time applications while YOLOv8 models are highly accurate and robust against challenging conditions. Each of these models will be discussed in the following subsections.

*1) YOLOv5:* The YOLOv5 model that used in this research consists of four parts which are input, backbone, neck and head as shown in Fig. 7. It utilizes CSP-Darknet53 with the Cross Stage Partial (CSP) strategy as its backbone to improve information flow and gradient issues [23]. YOLOv5 incorporates with a Spatial Pyramid Pooling (SPP) variant and uses BottleNeckCSP within the Path Aggregation Network (PANet) for the neck structure to enhance the receptive field and contextual feature extraction. The head of YOLOv5 models consists of three convolutional layers that predict bounding boxes, scores, and object classes.

*2) YOLOv8:* YOLOv8 is the improvised version of YOLOv5. Unlike YOLOv5 which uses anchor boxes, YOLOv8 is the improvised version of YOLOv5 where it uses different approach to detect the object by directly predicting the object centres. This approach helps to improved generalization and irregular shapes challenges. The YOLOv8 used the Spatial Pyramid Pooling Feature (SPPF) as a training technique to improve multi scale object handling. The YOLOv8 model also improve efficiency and flexibility while maintaining the performance by swapping the original larger Kernal size (6x6) convolution with a 3x3 in the stem. It also updates the core by swapping the C3 blocks with C2f. By concatenating features in the neck without the needs of identical channel dimension, the overall parameter counts and tensor size is reduced [23]. The SSD YOLOv8 model architecture is shown Fig. 8.

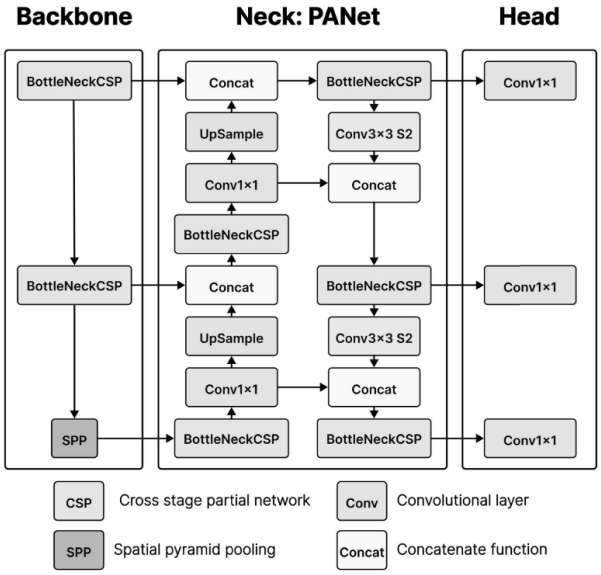



Fig. 7. Structure of YOLOv5 [24].

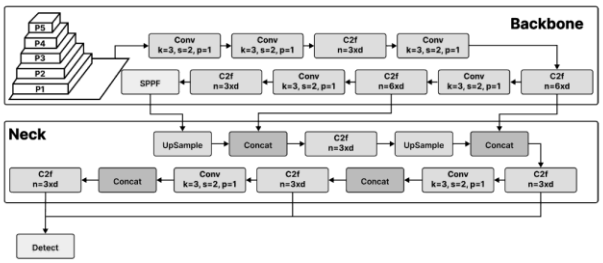



Fig. 8. YOLOv8 architecture structure [23].

## IV. EXPERIMENT

To demonstrate the reliability of the proposed model, a series of comprehensive experiments is conducted using Google Colab Notebook. Colab based on the Jupyter Notebook is used for machine learning computational operations and Python 3 with T4 GPU hardware accelerator in the runtime is also used in the experiment. The parameter settings for each of the models SSD and YOLO are configured with specific parameters as summarized in Table I. The file path for label map, training and testing data and TF records are set based on the storage location while the other parameters are kept unchanged. The number of classes is set to five classes. These five classes are set up based on the five vehicle types used to test the model which are ambulance, bus, car, motorcycle and truck.

Generally, the dataset consists of 1324 vehicles classified into five categories namely, ambulance, bus, car, motorcycle and truck are created. These images are then manually labelled to train the model. The PBXT files containing the respective class name are created for the purposes of training. Then the vehicle images and its label are converted into TF Record files which are in a sequence of binary format. After the process of labelling, the images are then split into the training and validation sets with a ratio of 80% images used as training set and the remaining 20% for the validation set. The aforementioned ratio is considered in this research since most of the work related to the deep learning models from literature use these ratios to split the data in their work [25]. Following these ratios, the training set consists of 1059 images while the remaining 265 images are used in the validation set. The details categories of the vehicle dataset used in this experiment are shown in Table II.

TABLE I. PARAMETERS SETTING OF SSD AND YOLO

| Model/ Parameter | SSD ResNet 50 | SSD ResNet 152 | SSD Mobile Net | YOLOv5 | YOLOv8 |
|---|---|---|---|---|---|
| Learning Rate | 0.04 | 0.04 | 0.04 | 0.01 | 0.01 |
| Weight | 0.0004 | 0.0004 | 0.0004 | 0.0005 | 0.001 |
| IoU threshold | 0.6 | 0.6 | 0.6 | 0.7 | 0.1 |
| Batch size | 4 | 4 | 4 | 16 | 16 |

TABLE II. VEHICLE DATASET CATEGORIES

| Vehicle Class | Number of Images |
|---|---|
| Ambulance | 158 |
| Bus | 312 |
| Car | 320 |
| Motorcycle | 248 |
| Truck | 286 |
| Total | 1324 |

## V. RESULTS

In this experiment, the classification performance is measured in terms of precision, recall and F1 Score. The computational time for each experiment is also recorded. Precision and recall are calculated by true positive, true negative, false positive and false negative value. True positive is the ability of the model to predict positive class correctly while, a true negative in which the model predicts the negative class correctly. On the other hand, false positive and false negative are the opposite from the true positive and true negative respectively. False positive occurs when the model incorrectly predicts the positive class while false negative occurs when the model incorrectly predicts the negative class. The formula for each of the performance measures is defined as follows:

$$\text{Precision} = TP/(TP+FP)$$

$$\text{Recall} = TP/(TP+FN)$$

$$\text{F1 score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall})$$

TP = True Positive, TN = True Negative

FP = False Positive, FN = False Negative

To evaluate the models, to find the most optimum result, the SSD models are trained with three numbers of training steps which are 10,000, 15,000 and 25,000. The YOLO models are trained with 25 epochs which are equivalent to 1,654 training steps. The training steps for YOLO models are calculated as in (1).

$$Training\ Steps = (Epoch \times Train\_Dataset)/Batch\ Size$$
$$= (25 \times 1059)/16$$
$$= 1654 \quad (1)$$

The results of SSD ResNet50, SSD ResNet152, SSD MobileNet, YOLOv5, and YOLOv8 model for the evaluation of each training step is shown in Table III.

TABLE III. COMPARISON RESULTS FOR SSD RESNET 50, SSD RESNET152, SSD MOBILENET, YOLOV5 AND YOLOV8 MODELS

| Model | Training Steps | Precision | Recall | F1 Score | Computational Time |
|---|---|---|---|---|---|
| SSD Resnet 50 | 10,000 | 0.257 | 0.370 | 0.3033 | 1h 37m 30s |
| SSD Resnet 152 | 10,000 | 0.408 | 0.473 | 0.4381 | 2h 25m 56s |
| SSD Resnet 50 | 15,000 | 0.325 | 0.433 | 0.371 | 4h 30m |
| SSD Mobile Net | 15,000 | 0.204 | 0.292 | 0.240 | 2h 59m 43S |
| SSD ResNet 50 | 25,000 | 0.264 | 0.363 | 0.305 | 1h |
| YOLOv 5 | 1645 | 0.909 | 0.944 | 0.926 | 10 mins |
| YOLOv 8 | 1645 | 0.956 | 0.968 | 0.968 | 30mins |

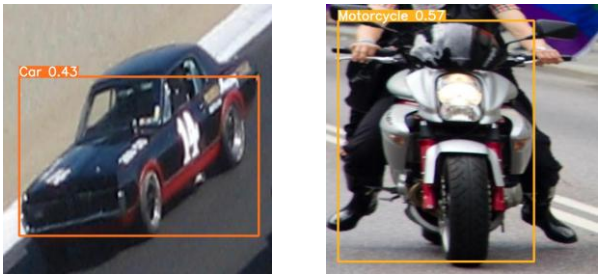
The SSD Resnet50 models which trained for all the three training steps of 10,000, 15,000 and 25,000 steps show low performance for all measure of precision, recall and f1 score. The high computational time is also observed for SSD Resnet50 in all training steps, which are 1h 37m 30s for 10,000 steps, 2h 25m 56s for 15,000 steps and 4h 30m for 25,000 training steps respectively. The SSD Resnet152 which trained for 10,000 steps also shows lower performance for all performance measure of precision, recall, f1 score including computational time compared to SSD Resnet50. For the training steps of 15,000 steps, SSD Resnet50 able to achieve high performance measure for all of precision, recall, f1 score and computational time compared to the SSD MobileNet. The less computational time is also observed in SSD Resnet50 compared to SSD MobileNet. On the other hand, both YOLO models which are YOLOv5 and YOLOv8 are trained with 1,654 training steps. From the experiment conducted, Both YOLO models able to obtain high performance measures for all precision, recall and accuracy with less computational time compared to all of the SDD models. The computational time of YOLOv5 model takes only 10 minutes while slightly minimal longer time taken is observed in YOLOv8 with only 20 minutes difference.

Among all the models tested, the YOLOv8 model achieved the highest performance measure for all precision, recall and F1 score with 0.956 precision, and 0.968 both recall and F1 score. This is followed by the YOLOv5 model with 0.909 precision, 0.944 recall and 0.926 F1 Score.

## VI. DISCUSSION

Overall, the YOLOv8 model outperformed others in detecting vehicle classification. Both of the YOLO models YOLOv5 and YOLOv8 outperform all of the SSD models which are SSD Resnet 50, SSD Resnet152, SSD MobileNet for all performance measure of precision, recall and f1 score including the computational time. The lower result obtained in all the SSD models is due to the drawbacks of the SSD approach that having difficulty to accurately detect on the small or far away vehicle. The SSD model relies on the lower-resolution feature maps for detecting small or far away vehicles, which sometimes may lack sufficient semantic information. Thus, the small or far away vehicle can be missed or misclassified. On the other hand, the YOLO model enhanced detection accuracy and robustness against challenging conditions including small object [26].

Among all the models tested, YOLOv8 able to achieve the highest performance measure for all precision, recall and F1 score with more than 0.956. This is followed by YOLOv5 with 0.909 of precision,0.944 recall and 0.926 F1score. Despite YOLOv8 able to detect vehicles in various conditions including vehicles in close proximity, far away and blur images, the low confidence score detection can still be observed on classic racing car and occluded motorcycle images as shown in Fig. 9.




(a) (b)

Fig. 9. Examples of the low confidence score detection (a) Classic racing car (b) Occluded motorcycle images.

## VII. CONCLUSION

The YOLOv8 model is proposed for vehicle classification to classify between types of vehicles in smart city with a goal to provide intelligent solutions for road traffic monitoring. This can be achieved using accurate predictive data analytics for future action planning and decision making. The result shows that the model YOLOv8 able to effectively classify types of vehicles including vehicles in close proximity, far away and blur images. Therefore, it can be used to provide intelligent solutions to improve road traffic system for smart city. Though the YOLOv8 model is superior compared to other models and achieves more accurate classification, the method was shown to be less effective in detecting some of the vehicle images as shown in VI. In the future, we will concentrate on improving these drawbacks by increasing the diversity of vehicle images dataset by using data augmentation techniques for more advanced deep learning methods.

## ACKNOWLEDGMENT

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# Using EPP Theory and BMO-Inspired Approach to Design a Virtual Reality Dashboard Design Ontology

Liew Kok Leong[1], Fazita Irma Tajul Urus[2], Muhammad Arif Riza[3],
Mohammad Nazir Ahmad[4], Ummul Hanan Mohamad[5]
Institute of Visual Informatics, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia[1, 2, 3, 4, 5]
i-AI UKM Research Group, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia[4, 5]
Infrastructure University Kuala Lumpur (IUKL), 43000, Kajang, Selangor, Malaysia[4]

***Abstract*—This paper introduces the Virtual Reality Dashboard Design Ontology (VRDDO), an ontological framework developed to address the absence of standardized methodologies in designing Virtual Reality (VR) dashboards for complex data visualization, particularly in smart farm monitoring. The VRDDO is built upon the Design Science Research (DSR) approach and anchored in Kernel Theory, specifically the Ecological Psychological Perspective (EPP) theory and Business Model Ontology (BMO). During the design and development phase of DSR, the Unified Ontological Approach (UoA) is applied as the ontology development methodology, to design and construct VRDDO as a design artifact. By offering a structured framework for VR dashboard design, VRDDO aims to enhance data interpretation and decision-making in immersive environments. Additionally, this ontology forms the basis for a Virtual Reality Dashboard Design Method, establishing a systematic and user-centric approach to developing efficient VR dashboards. This research is significant for its potential to improve VR dashboard development across diverse domains, facilitate knowledge sharing, and eliminate fragmented, ad-hoc practices in immersive data visualization.**

***Keywords*—Design Science Research (DSR); Ontology Development Methodology (ODM); Ecological Psychological Perspective (EPP); Unified Foundational Ontology (UFO); Virtual Reality Dashboard Design Method (VRDDM)**

## I. INTRODUCTION

Virtual Reality (VR) technology has rapidly evolved in recent years, revolutionizing numerous fields including education, healthcare, entertainment, and business. As VR applications become more sophisticated, the need for effective data visualization and interaction within these immersive environments has grown exponentially. VR dashboards have emerged as a powerful tool to address this need, providing users with intuitive and immersive interfaces to monitor, analyze, and interact with complex data sets. The author in [1] defines a dashboard as "a predominantly visual information display that people use to rapidly monitor current conditions that require a timely response to fulfill a specific role". In the context of VR, these dashboards take on new dimensions, leveraging the unique capabilities of immersive environments to present information in ways previously impossible in traditional 2D interfaces.

The development of VR dashboards involves a complex interplay of various technologies and data sources. These dashboards can integrate data from Internet of Things (IoT) devices, such as sensors and microcontrollers, as well as from open-source databases, big data repositories, and manually gathered information. User input can be collected through various means, including graphical user interfaces (GUIs), VR equipment like head-mounted displays (HMDs) and eye gaze trackers, smartphones, and even physiological sensors like heart rate monitors [2-9]. This diversity of data sources and input methods presents both opportunities and challenges in VR dashboard design and development.

While the widespread adoption of dashboards in various industries has demonstrated its value in improving information comprehension and decision-making, the design of effective VR dashboards remains subject to numerous challenges. Common issues include poor use of virtual space, presentation of insufficient information, and unappealing visual elements that can detract from the user experience. The complexity of mobility data and the unique characteristics of VR environments necessitate a more nuanced approach to dashboard design than traditional 2D interfaces. For complex systems particularly in smart farm monitoring, developers must consider not only the type, volume, and frequency of data updates but also the specific purpose of the dashboard and the needs of its intended users [10, 11]. There is a lack of standardization in designing VR dashboards for smart farming applications. More broadly, the field would benefit from a unified Virtual Reality Dashboard Design Method (VRDDM). Establishing such standards would simplify the design process and reduce complications for developers. The establishment of a Virtual Reality Dashboard Design Ontology (VRDDO) aims to address this need by providing a theoretical framework that can guide developers in creating more effective, user-friendly, and standardized VR dashboard solutions. By establishing common principles and design patterns, VRDDO has the potential to accelerate innovation in this field, improve user experiences, and ultimately enhance the value of VR applications across various domains.

Motivated by the growing demand for immersive data visualization, this study proposes the VRDDO to address the lack of standardized VR dashboard development methods. The VRDDO benefits include enhancing decision-making, improving user engagement, and creating structured design processes adaptable across domains. Our main contributions are the construction of VRDDO based on theories of EPP and BMO and integration with the Unified Ontological Approach (UoA) and Unified Foundational Ontology (UFO).

The remainder of this paper is structured as follows: Section II reviews background and theories. Section III describes the theory used. Section IV proposes the VRDDO framework. Section V concludes the study.

## II. BACKGROUND

### A. Design Science Research

Design Science Research (DSR) has emerged as a crucial paradigm in Information Systems (IS) research, complementing the more traditional behavioral science approach. While behavioral science focuses on developing and verifying theories that explain or predict human and organizational behavior, DSR aims to extend the boundaries of human and organizational capabilities through the creation of innovative artifacts. This paradigm is particularly relevant in the context of IS research, which sits at the intersection of people, organizations, and technology. DSR provides a structured approach to understanding, executing, and evaluating research that results in tangible, practical outcomes. In the case of the Virtual Reality Dashboard Design Ontology (VRDDO), DSR offers a methodological framework that guides the design and development of this innovative artifact, ensuring that it is both theoretically grounded and applicable [12, 13, 32].

The Design Science Research Methodology (DSRM) provides a systematic process for conducting DSR, emphasizing the importance of theory-based grounding in the development of design artifacts. This approach is particularly relevant for the VRDDO, which is positioned as a design artifact resulting from the DSR methodology, specifically emerging from the Design & Development stage. The VRDDO aligns with the perspective of DSR practitioners who advocate for kernel theory-based grounding in artifact design and development. By incorporating kernel theories as mandatory components of the DSR methodology, the VRDDO gains a solid theoretical foundation that enhances its validity and applicability. This theoretical grounding not only ensures that the VRDDO is built upon established principles but also facilitates its integration into the broader context of VR dashboard design and development. Through this approach, the VRDDO aims to bridge the gap between theoretical knowledge and practical application, offering a comprehensive framework that can guide researchers and practitioners in creating more effective and standardized VR dashboard solutions.

### B. DSR for the Development of VRDD

Building upon the discussion of Design Science Research (DSR) and its methodology (DSRM), it is crucial to explore the various perspectives on the role of kernel theories in the development of design artifacts. Within the DSR field, there are three distinct "schools of thought" regarding the necessity and importance of kernel theories in artifact design and development. Fig. 1 shows the position of each school taught in their beliefs towards whether kernel theories are required for grounding and whether design theories can be accepted as key artifacts [14]. These perspectives offer valuable insights into the theoretical grounding of artifacts like the Virtual Reality Dashboard Design Ontology (VRDDO).

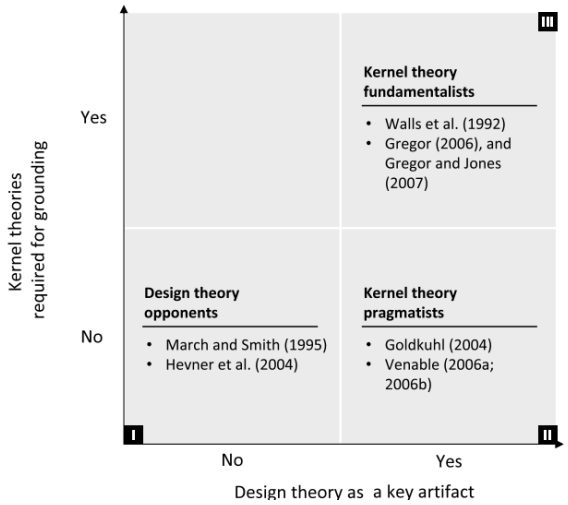


Fig. 1. DSR school of thought [14].

The first school, known as "Design Theory Opponents" (DTO), posits that kernel theories are not mandatory in DSR artifact development. Pioneered by DSR founders in Information Systems (IS) such as [13, 15], this perspective argues that DSR complements Behavioural Science (BS) rather than replicating it. While kernel theories are prevalent in BS research, they are not considered a priority or necessity in DSR. The author in [13] stated that while knowledge from behavioral sciences and design science research may be used in constructing design science artifacts, IS DSR artifacts do not necessarily need to be grounded in kernel theories. This school of thought does not accept theory as an output of DSRM and does not emphasize the need for kernel theories in artifact engineering.

The second perspective, termed "Kernel Theory Pragmatists" (KTP), takes a middle-ground approach. Established by [16-18], this school suggests that while kernel theories are not crucial in the artifact construction process, theory as an output of DSRM is acceptable as an impact and result of the research. This pragmatic stance allows for flexibility in the use of theories within DSR projects.

The third and most stringent perspective is the "Kernel Theory Fundamentalist" (KTF) school, championed by [19-21]. This approach mandates the use of kernel theories in artifact construction and simultaneously accepts theory as an output of DSRM. The author in [19] emphasized that kernel theories from natural or social sciences serve as a foundation for artifact construction. This school of thought insists on rigorous theoretical grounding for all aspects of DSR.

In the context of the VRDDO development, the researcher has adopted a balanced approach, acknowledging the existence and potential contributions of all three schools of thought. While recognizing the arguments against the necessity of kernel theories presented by the DTO and KTP schools, the researcher leans towards the KTF perspective in accepting the involvement of kernel theories in the artifact construction process. However, the researcher does not fully align with the KTF view that theory must be an output of DSRM. This nuanced approach allows for a theoretically grounded

development of the VRDDO while maintaining flexibility in the research outcomes.

By considering these diverse perspectives on the role of kernel theories in DSR, the development of the VRDDO can benefit from a rich theoretical foundation while avoiding overly rigid constraints. This balanced approach ensures that the VRDDO is developed with a solid theoretical grounding, enhancing its validity and applicability in the field of VR dashboard design. Furthermore, it demonstrates the complexity and ongoing debates within the DSR community, highlighting the importance of thoughtful consideration of theoretical foundations in the development of innovative artifacts like the VRDDO.

## III. THEORY USED

In developing the VRDDO, this study adopts the Kernel theory pragmatist perspective by implementing two theories suited for the ontological design of VR. The theories are based on business model ontology (BMO) design for the development of business model canvas (BMC) [22, 33]. The Business Model Ontology (BMO), developed by Alexander Osterwalder, provides a structured framework for representing, understanding, communicating, and analyzing business models. It addresses the challenge of defining business models by offering a common language and conceptual structure. The BMO served as the foundation for the widely adopted Business Model Canvas (BMC), a visual tool for describing, designing, and innovating business models. In the context of the Virtual Reality Dashboard Design Ontology (VRDDO), the BMO's approach to structuring complex business concepts has inspired a similar ontological approach to VR dashboard design. As one of the grounding theories for VRDDO, the BMO demonstrates the power of ontologies in creating standardized frameworks for complex domains, guiding the development of a comprehensive and adaptable structure for VR dashboard design principles.

In designing the BMC, key blocks are established based on the common characteristics/elements that exist from other business models [22, 23]. Semantics that relate each of the key blocks help to establish the concepts well in developing the ontology of a business model. Therefore, this approach will also serve as one of the grounded theories within this work in developing VRDDO.

Another major grounding theory that was applied to this study for VRDDO development is the theory of ecological psychological perspective (EPP) [24]. The theory emphasizes direct perception of environmental affordances which features suggestions on how to interact with objects. This active perception model views senses as interconnected, information-seeking mechanisms. In Virtual Reality Dashboard Design Ontology (VRDDO) development, EPP provides crucial insights into user perception and interaction within virtual environments. Combined with the Business Model Ontology (BMO), EPP informs the design of intuitive, exploration-friendly VR dashboards. By considering affordances in virtual spaces, VRDDO can create more natural and meaningful interactions, enhancing user engagement and information comprehension. This synthesis enables a comprehensive approach to VR dashboard design, grounded in both perceptual psychology and structured business concepts.

### A. Narrative Literature Review (NLR) for Deriving Key Blocks for Ontology Design

The proposed VRDDO has to be built with established key blocks depending on its application. The targeted application for the VRDDO is on smart farm monitoring application. Therefore, several key blocks that serve as essential elements for the VRDDO are identified via literature study. The NLR is conducted in a manner that identifies commonalities of each element. In other words, common elements that have been found in other VR dashboard design methods are selected for use as key blocks.

### B. Ontology Design Using a Unified Ontological Approach (UoA)

The Unified Ontological Approach (UoA) [25, 34] is a framework for ontology development that synthesizes the strengths of various Ontology Development Methods (ODMs) and draws inspiration from successful ontologies like Business Model Ontology (BMO). This approach aims to streamline the ontology development process by integrating common characteristics and key steps found across different methodologies. The UoA emphasizes iterative development, consistent notation, flexible formalization, reusability, scenario-driven customization, and comprehensive structural representation.

The development of the UoA was facilitated through a Narrative Literature Review (NLR) method. This approach allowed for a comprehensive and interpretative synthesis of existing literature related to ODMs. The NLR method is particularly well-suited for addressing complex and emerging fields, enabling researchers to explore topics in broader ways. Through this method, researchers identified common steps and practices across different ODMs, cross-referenced these findings with the principles of successful ontologies like the BMO, and integrated these insights to create the UoA framework.

The UoA is particularly suitable for building the Virtual Reality Dashboard Design Ontology (VRDDO) due to several key factors. First, its emphasis on scenario-driven development aligns well with the diverse use cases and applications of VR dashboards across different domains. This approach ensures that the VRDDO will be relevant and applicable in real-world contexts. Second, the flexible formalization approach allows for the VRDDO to adapt to the rapidly evolving field of VR technology and dashboard design principles. Third, the focus on reusability and reengineering enables the VRDDO to leverage existing knowledge in related fields, such as information visualization and human-computer interaction, while still allowing for VR-specific adaptations.

Furthermore, the UoA's comprehensive structural representation ensures that the VRDDO can capture both the structural and dynamic aspects of VR dashboard design, which is crucial given the interactive and immersive nature of VR environments. The iterative process embedded in the UoA also allows for continuous refinement of the VRDDO, ensuring it remains up to date with advancements in VR technology and

design practices. By adopting the UoA for the development of the VRDDO, researchers can create a robust, flexible, and comprehensive ontology that effectively captures the complexities of VR dashboard design while ensuring its applicability and adaptability across various domains and use cases.

### C. Importance of ODM for Building VRDDO

The Unified Ontological Approach (UoA) is used for building the Virtual Reality Dashboard Design Ontology (VRDDO). As a synthesis of various Ontology Development Methods (ODMs) and inspired by successful ontologies like Business Model Ontology, the UoA offers a robust framework for developing the VRDDO. Its key features - iterative development, consistent notation, flexible formalization, reusability, scenario-driven customization, and comprehensive structural representation - are particularly well-suited for the complex and evolving field of VR dashboard design.

UoA's scenario-driven approach ensures the VRDDO remains relevant across diverse use cases, while its flexible formalization allows adaptation to advancing VR technologies. The focus on reusability enables leveraging existing knowledge from related fields while accommodating VR-specific requirements. Comprehensive structural representation is essential for capturing both structural and dynamic aspects of VR dashboard design, crucial for representing the interactive nature of VR environments. The iterative process allows for continuous refinement, ensuring the VRDDO stays current with VR advancements. By employing the UoA, researchers can create a robust, flexible, and comprehensive ontology that effectively captures VR dashboard design complexities while ensuring adaptability across various domains, ultimately driving progress in VR dashboard design and its applications.

## IV. VRDDO

The Virtual Reality Dashboard Design Ontology (VRDDO) shown in Fig. 2 is considered the 'backbone' of the Virtual Reality Dashboard Design Method (VRDDM), which aims to address the lack of standardized approaches in designing VR information dashboards, particularly in the context of smart farm monitoring. Developed using a Unified Ontological Approach (UoA), the VRDDO serves as a structured framework to capture commonalities identified across various dashboard design-related works. This ontology forms the theoretical foundation of the VRDDM, providing a systematic and standardized method for creating immersive VR information dashboards that can effectively tackle monitoring challenges in smart farming and potentially other domains.

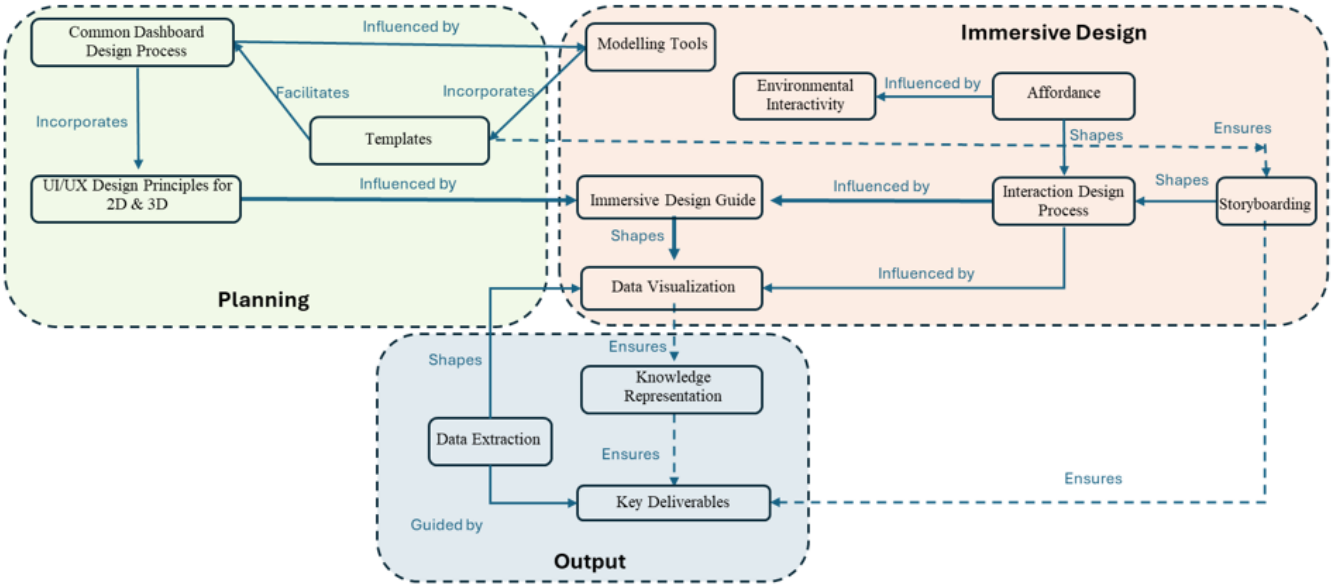


Fig. 2. Proposed VRDDO with concepts derived from key blocks.

The VRDDO is developed through a comprehensive process that begins with a narrative review of existing literature to identify common elements and best practices in dashboard design. These commonalities which are considered key blocks of VR dashboard designs are then formalized using the UoA, which allows for a systematic organization of concepts, relationships, and design principles specific to VR dashboard creation. By incorporating insights from various sources and methodologies, the VRDDO aims to create a robust and flexible framework that can guide the design and development of VR dashboards across different applications. This standardized approach offered by the VRDDO is particularly significant in the context of smart farm monitoring, where effective visualization and data presentation are crucial for decision-making and maintaining high-quality agricultural production. The ontology not only facilitates the design process but also promotes knowledge sharing and reuse, potentially eliminating ad-hoc practices in VR dashboard development. While the current focus of the VRDDO is on smart farm monitoring, its structured approach and foundation in common design principles suggest a potential for adaptation and application in other domains, opening avenues for future research to explore its versatility and robustness across various fields requiring immersive data visualization and monitoring solutions.

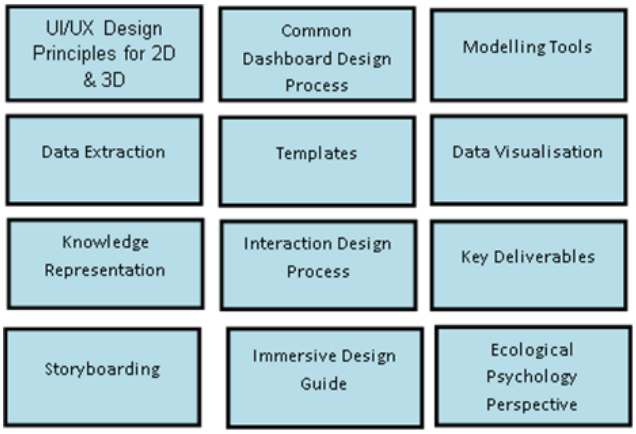


Fig. 3. Related key blocks derived from NLR.

### A. Concepts and Semantics to form VRDDO

The Virtual Reality Dashboard Design Ontology (VRDDO) is structured around twelve key blocks as shown in Fig. 3, each serving as a fundamental concept in the design and development of VR dashboards. These blocks collectively form a comprehensive framework that guides the creation of effective and user-centric VR dashboards. Explanation of each block and its role as a concept in the VRDDO as below:

UI/UX Design Principles for 2D and 3D: This block emphasizes the importance of user interface and user experience design in both 2D and 3D environments. It incorporates five main principles: scale, visual hierarchy, balance, contrast, and gestalt. These principles ensure that the VR dashboard is not only visually appealing but also intuitive and easy to navigate [26]. As a concept in the VRDDO, this block provides guidelines for creating immersive and user-friendly interfaces that leverage the unique capabilities of VR environments. In the VRDDO, this concept influences the immersive design guide.

Common Dashboard Design Process and Templates: This block outlines a standardized process for designing VR dashboards, including steps like requirements gathering, data processing, UI/UX design, and implementation. It also emphasizes the use of templates to streamline the design process and ensure consistency across different dashboard projects. Thus, templates as a concept facilitate the design process in providing a structured approach to VR dashboard development.

Data Extraction/Data Collection: This block focuses on the methods and processes of gathering and extracting data for visualization in the VR dashboard. It covers various data sources such as IoT devices, questionnaires, GUI inputs, VR equipment, smartphones, and sensors. The concept emphasizes the importance of adhering to data protection regulations and using appropriate tools and algorithms for accurate data extraction and classification where applicable.

Domain Model and Knowledge Representation: This block introduces the concept of ontology in the context of VR dashboard design. It highlights the need for a structured and semantically rich representation of the knowledge domain, which is crucial for creating interactive and meaningful VR dashboards. The VRDDO itself is a manifestation of this concept, providing a formal specification of the concepts and relationships within the VR dashboard design domain.

Interaction Design (IxD) Process: This block focuses on the user-centric design approach, emphasizing the importance of understanding user needs and behaviors when interacting with VR dashboards. The five stages of the IxD process (discovering user needs, analyzing, designing solutions, prototyping, and deploying) form a crucial concept in the VRDDO, ensuring that the resulting dashboards are highly usable and meet user requirements [27].

Data Visualization and Modelling Tools: This block covers the various tools and techniques used for visualizing and modeling data in VR environments. It acknowledges the complexity of VR systems, including hardware components and software requirements. As a concept in the VRDDO, this block guides developers in selecting and utilizing appropriate tools for creating effective data visualizations in VR.

Storyboarding: This block emphasizes the importance of pre-visualization techniques in VR dashboard design. Storyboarding helps in planning the user's journey through the virtual environment and their interactions with data displays [28]. As a concept in the VRDDO, storyboarding serves as a crucial step in crafting a cohesive narrative for data exploration and optimizing the user experience.

Ecological Psychology Perspective: Acting as one of the grounding theories for the VRDDO, this block incorporates the EPP theory of affordances into VR dashboard design. It emphasizes the importance of creating intuitive, exploration-friendly virtual environments where users can directly perceive and interact with information. This perspective guides the design of VR dashboards to leverage Natural perceptual systems, enabling users to navigate and comprehend complex data more effectively. This key block provides two concepts in the VRDDO which are affordances and environmental interactivity. Affordances are the possibilities that an environment or object offers to an organism, particularly a human. They are directly perceivable properties that suggest how something can be used or interacted with, such as a handle affording grasping or a flat surface affording sitting. Affordances are relational, depending on both the properties of the object or environment and the capabilities of the organism perceiving them. Therefore, environmental interactivity is the dynamic relationship between an individual and their surroundings, where the environment offers opportunities for action and engagement. It encompasses how people perceive, interpret, and respond to the possibilities for interaction presented by their environment [29]. In the context of VR dashboards, environmental interactivity focuses on designing virtual spaces that intuitively communicate how users can interact with and manipulate data, leveraging natural perceptual cues to enhance user engagement and understanding.

### B. Restructuring of VRDDO Under UFO

The development of the VRDDO employed the Unified Ontological Approach (UoA), as proposed by [25], as the primary Ontology Development Method (ODM). The UoA was specifically chosen for its ability to integrate various

ontology development approaches while maintaining flexibility for domain-specific adaptations. This structured approach facilitates systematic progression from problem identification to ontology implementation and validation, ensuring both theoretical rigor and practical applicability. The UoA framework comprises nine iterative steps: (1) identifying the scope and purpose, (2) defining and identifying concepts, (3) organizing concepts, (4) defining properties and constraints, (5) formalizing the ontology, (6) implementing and testing, (7) evaluating the ontology, (8) documenting the ontology, and (9) maintaining and evolving the ontology. These steps enable the iterative refinement of the ontology throughout its lifecycle, ensuring that the resulting framework aligns with its intended purpose and can adapt to future changes.

The implementation process utilized UML for initial conceptual modeling, followed by OntoUML for ontological formalization. This combination provided the necessary rigor for developing a semantically rich and well-founded ontology while maintaining practical applicability. OntoUML, an extension of UML enriched with ontological principles from the Unified Foundational Ontology (UFO), was chosen for its ability to enhance the ontological adequacy of conceptual models [30]. The formalization process included syntactical validation using the OntoUML Plugin in Visual Paradigm, ensuring that the VRDDO framework was free of errors and adhered to formal modeling principles. After the implementation of UFO in the preliminary VRDDO, the relationship between concepts is clarified further. Fig. 4 shows the iterated VRDDO with UFO implementation.

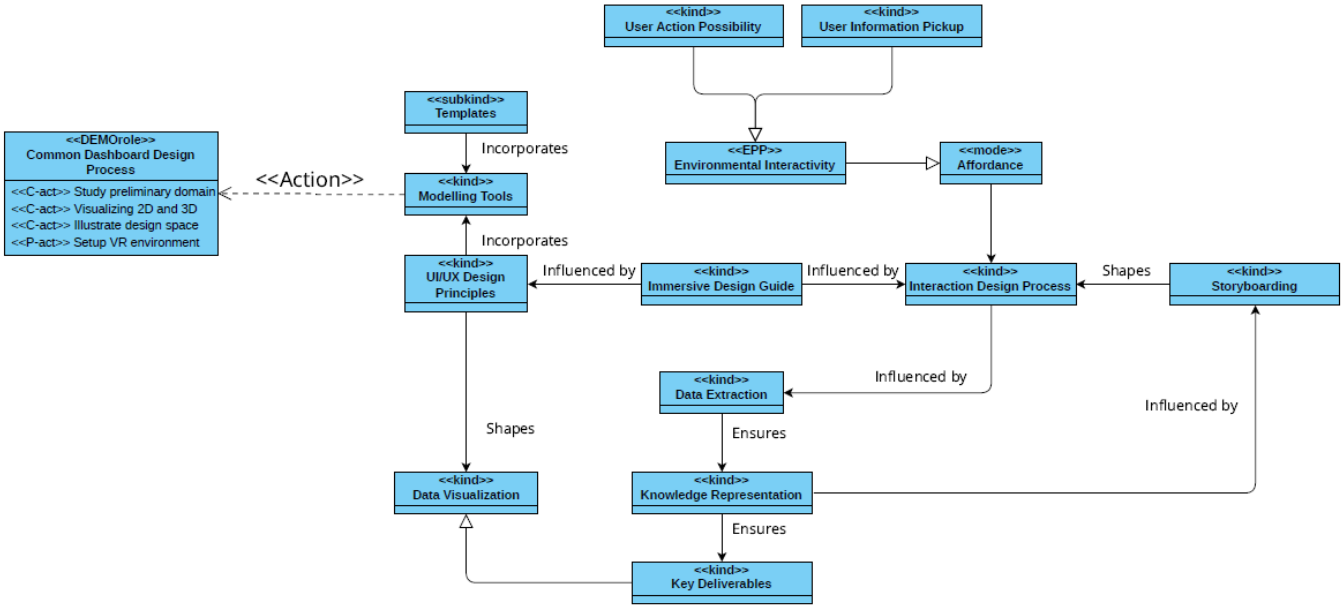


Fig. 4. Proposed VRDDO with concepts derived from key blocks.

VRDDO, with the implementation of UFO, prompts the introduction of two new concepts. These concepts further define the ecological psychological perspective (EPP) theory and how it will be part of the VRDDO to contribute towards achieving affordance and shape the interaction design process. The 2 concepts are both classified as <<kind>>. One concept, which is User action possibility refers to what are possible actions or gestures that the user can do to interact with the object within the 3D VR dashboard. Another concept is known as User information pickup. This concept refers to how the user can know that an object within the VR environment can be interacted with. The concept emphasizes the need for VR dashboard designers and developers to incorporate a self-explanatory design for objects such as information windows within the VR environment for users. Therefore, with the implementation of the EPP theory, it is known that to achieve greater immersion, designers will have to design interactable objects that are both self-explanatory and offer freedom of interaction between users and the VR dashboard. Immersion can achieve greater delivery and clarity for users, especially with a dense amount of information to display within a VR environment.

The implementation of these concepts within the VRDDO framework has far-reaching implications for the future of interaction design. As VR environments grow more complex, the ability to display dense information while maintaining user clarity and immersion becomes paramount. Incorporating EPP-driven principles enables designers to craft interactable objects that balance freedom of interaction with clarity of purpose. This balance is particularly critical in applications such as education, healthcare, and data visualization, where the delivery of accurate and easily interpretable information is essential. For example, in medical training simulations, VR dashboards equipped with self-explanatory interactive elements can enhance the learning experience by providing real-time feedback and reducing cognitive overload. Similarly, in business analytics, immersive dashboards can facilitate better decision-making by allowing users to intuitively explore large datasets. These advances contribute to achieving higher levels of immersion, which research identifies as a key factor in improving information retention and user satisfaction in VR environments [31]. Ultimately, the VRDDO's integration of EPP theory with the UFO approach paves the way for a new era of human-centered VR design, where interactivity and

intuitiveness coalesce to deliver transformative user experiences. Table I describes the rationale of each concept in the VRDDO. Compared to existing VR dashboard designs, VRDDO offers a standardized, theory-driven framework with clearer user interaction pathways and enhanced immersive data comprehension. Validation via integration of the Ecological Psychological Perspective (EPP) theory ensures better affordances and environmental interactivity for users.

TABLE I. CONCEPTS WITH IMPLEMENTED UPPER ONTOLOGIES

| Concepts | Upper Ontology | Rationale |
|---|---|---|
| Common Dashboard Design Process | <<DEMOrole>> | Emphasizes the progressive, temporal nature of the design process with distinct stages of development. |
| Modeling Tools | <<kind>> | Defines the fundamental structures for representing VR dashboard elements, ensuring consistency in visualization and interaction modeling. |
| Templates | <<subkind>> | Acts as pre-designed frameworks that align with standardized dashboard layouts, aiding in efficient UI/UX development. |
| UI/UX Design Principles for 2D & 3D | <<kind>> | Guides the visual and interactive elements by leveraging VR affordances to create an intuitive and immersive user experience. |
| Environmental Interactivity | <<EPP>> | Describes how the dashboard allows dynamic engagement with virtual elements, ensuring real-time feedback and adaptability in VR environments. |
| Affordance | <<mode>> | Refers to the perceived action possibilities within the VR interface, shaping user expectations and interactions in the system. |
| Immersive Design Guide | <<kind>> | Provides structured methodologies for designing VR dashboards, ensuring users are effectively engaged within the virtual environment. |
| Data Extraction | <<kind>> | Focuses on gathering and structuring relevant data for visualization and interaction, crucial for informed decision-making in VR dashboards. |
| Interaction Design Process | <<kind>> | Defines the workflow of user interactions with the VR dashboard. |
| Storyboarding | <<kind>> | Facilitates the planning of dashboard workflows by visually representing interaction sequences and possible user journeys. |
| Knowledge Representation | <<kind>> | Encapsulates how domain knowledge, actions, and entities are structured within the VR dashboard ontology, ensuring meaningful data organization. |
| Data Visualization | <<kind>> | Translates complex data into graphical representations that enhance user comprehension and decision-making within the VR space. |
| User action possibility | <<kind>> | Describes how a user can interact with objects (Gestures, other methods of input, etc.). |
| User information pickup | <<kind>> | Describes how a user can know whether an object is interactable. |
| Key Deliverables | <<kind>> | Outlines the critical outcomes expected from the VRDDO framework, aligning with both technical and design perspectives. |

### C. VRDDO Iteration

The iterative refinement of the Virtual Reality Dashboard Design Ontology (VRDDO) aligns with the principles of the Design Science Research (DSR) methodology, which emphasizes a cyclical process of development and evaluation to enhance the robustness and applicability of a design artifact [12]. The transition from the initial VRDDO (Fig. 2) to its refined version incorporating the Upper Foundational Ontology (UFO) (Fig. 4) was driven by successive iterations, ensuring improved conceptual clarity, semantic consistency, and structural coherence. Iterative design is fundamental in ontology engineering, as it allows for the continuous integration of theoretical insights, stakeholder feedback, and empirical validation, thereby fostering ontological rigor and practical relevance. By incorporating UFO, the final VRDDO iteration achieves a higher level of abstraction and interoperability, facilitating a more precise representation of immersive design processes. This iterative approach underscores the necessity of refinement cycles in advancing domain-specific ontologies, ensuring alignment with foundational theories, and enhancing applicability across VR-driven environments.

Compared to existing VR dashboard development approaches [3, 4, 7, 8], which often rely on ad-hoc design practices or lack structured theoretical foundations, the VRDDO offers a standardized, reusable, and theory-driven framework grounded in kernel theories and ontological principles. By leveraging the Unified Ontological Approach (UoA) and integrating the Ecological Psychological Perspective (EPP), the VRDDO ensures that both structural and perceptual aspects of dashboard design are systematically addressed. This approach enhances user immersion, data comprehension, and design scalability, distinguishing VRDDO from conventional methods that typically overlook these multidimensional factors.

### D. The way Forward for the VRDDO

This study successfully formalized the Virtual Reality Dashboard Design Ontology (VRDDO) based on the Unified Ontological Approach (UoA), EPP theory, and BMO principles. The developed ontology organizes 12 key concepts and demonstrates how affordances and user-centered designs improve information visualization within VR environments. The proposed VRDDO helps to establish and reveal key relationships between concepts that are essential to be considered during the design and development of a VR dashboard. This work is inspired by Osterwalder's work in the creation of the BMC. The BMC is derived from BMO which consists of building blocks. Hence, The VRDDO will be used in our next work to establish a VR dashboard design method (VRDDM). A more detailed discussion on the development of VRDDM will be presented in our future publications.

## V. CONCLUSION

The Virtual Reality Dashboard Design Ontology (VRDDO) presents a promising framework for standardizing and enhancing the development of VR dashboards, particularly in the context of smart farm monitoring. By synthesizing various ontology development methods and drawing inspiration from successful models like Business Model Ontology, the VRDDO

offers a robust, flexible, and comprehensive approach to VR dashboard design. The incorporation of key theories, such as Gibson's Ecological Psychological Perspective, ensures that the ontology addresses both technical and perceptual aspects of VR interactions. The VRDDO's structured approach, emphasizing iterative development, consistent notation, and scenario-driven customization, provides a solid foundation for creating intuitive and effective VR dashboards. As the backbone of the forthcoming Virtual Reality Dashboard Design Method (VRDDM), the VRDDO has the potential to significantly improve the design and implementation of VR information dashboards across various domains, promoting standardization and knowledge sharing in this rapidly evolving field. While the VRDDO effectively formalizes the key structural elements necessary for VR dashboard design (an endurant perspective), less emphasis was placed on modeling dynamic, time-based interactions (a perdurant perspective). Future research can enhance ontology by incorporating dynamic behavior modeling to address evolving user interactions and real-time data visualization needs in VR environments.

## VI. Future Work

Future research will focus on extending the Virtual Reality Dashboard Design Ontology (VRDDO) to incorporate perdurant perspectives, enabling dynamic modeling of time-based user interactions, adaptive interface behaviors, and evolving data visualization within VR environments. By integrating concepts that represent events, processes, and temporal affordances, the ontology can better capture the fluid and interactive nature of immersive VR experiences. Additionally, empirical validation across multiple domains such as healthcare, education, and urban planning will be conducted to evaluate the adaptability and effectiveness of the enhanced VRDDO framework. This progression aims to transform VRDDO into a comprehensive standard for both static and dynamic VR dashboard design across diverse applications.

## Acknowledgment

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# Quantitative Assessment and Forecasting of Control Risks in the Ore-Stream Quality Management System

Almas MukhtarkhanulySoltan[1], Bakytzhan Turmyshevich Kobzhassarov[2]
Senior lecturer, School of Digital Technologies and Artificial Intelligence, EKTU named after D. Serikbayev, Ust-Kamenogorsk, Republic of Kazakhstan[1]
Doctoral Student, School of Digital Technologies and Artificial Intelligence, EKTU named after D. Serikbayev, Ust-Kamenogorsk, Republic of Kazakhstan[2]

***Abstract*—The paper is aimed at organizational and technological optimization of the system of remote control of ore-stream quality according to technical and economic criteria. The ore-stream in the environment of digital transformation of the mining industry is seen as a system where one of the main functions of management is control. The key importance of the control function in ore-stream quality management becomes in ore quality assessment at the stage of ore material technological preparation, where the homogeneity of the ore massif in terms of the content of the useful component from heterogeneous deposits is formed. Such component in the paper is iron. System technological novelty, which is presented in the paper, consists in realization of constant remote control of ore material quality in the form of monitoring. Remote control is technically realized using unmanned vehicles with subsequent digital processing of information by on-board microprocessor technology and special mathematical and software. The iron content of the ore is estimated from the vertical vector of the magnetic field of the ore material. The implementation of such a concept envisaged the solution of the following tasks: development of a structural and functional model of ore-stream quality control; development of mathematical support for the digital system of data processing of ore material magnetic field measurement data, optimization of metrological indicators of the measuring complex of the control system. It is proposed to use control risks as criteria for quantitative assessment of the functional quality of the ore-stream quality management system. The empirical function of the relationship between the cost of magneto metric remote control of iron content and probable control risks is found. A 3D model of the dependence of the cost of magnetometric control of iron content as a function of accuracy and the value of standards of iron content in ore was built.**

***Keywords*—Ore-stream; system; model; technology; control; risks; probability; unmanned vehicles***

## I. INTRODUCTION

The aim of the work is organizational and technological optimization of the system of remote control of ore-stream quality according to technical and economic criteria. The achievement of the goal is proposed to be solved by developing information and analytical support for the ore-stream quality control system. The proposed study addresses two contextualized scientific and practical challenges that bridge the gaps of known studies: development of a structural and technological model of remote ore quality control and formalization of the process of quantitative assessment of control risks and decision-making under conditions of parametric vagueness of control agents and statistical uncertainty of technological data. Moreover, it is extremely important to differentiate the risks by the degree of their impact on the socio-economic activity of the mining enterprise [1.4].

One of the working and dominant hypotheses proposed in this research relies on the paradigm that decision quality is a systemic convergence of heterogeneous technological agents, where the control system, which finalizes almost every managerial decision, plays a decisive role.

This paper focuses on the function of digital remote control of ore-stream quality. The structural and functional model of the system digital support of the control process contains the following system components: technical support; mathematical support, software, information support, metrological support, organizational and methodological support.

The paper deals with the technology of remote control of iron ore quality. Ore quality in this paper is assessed by the percentage of iron content in a ton of ore material. In real production practice, an ore massif of controlled material is distributed on a solid base in the form of a rectangular ore body of 100x900 m. in the open air. This massif is called an “ore yard”. Measurement of iron level in the ore material is carried out by magnetometers according to the controlled value of magnetic field strength with a technological step of 10 m. over the entire area of the “ore yard”. An estimate of ore material quality is traditionally the average value of magnetic field strength in point coordinates of measurement $Y_{ij}$ over the entire ore mass area in the ore yard. Control and measurement operations are accompanied by control errors, which are called risks and are differentiated by their economic content into “producer risk” and “consumer risk”. Such differentiation of risk is essential, as these types of risk lead to different socio-economic consequences in practice. Currently, the need for risk assessment in any project and production activity is regulated by the ISO 2015 version of the standard, which has a special supplement - IEC 31010 “Risk Management”. The main difference between this addition to the standard and previous versions of ISO is that “risks are no longer implicit in the standard, risk assessment is now embedded in the management system and becomes an inherent feature of it”. The problem of quantitative assessment of these risks in practice is that there is no possibility of instrumental measurement of these risks or by the method of statistical processing, but only by formal mathematical and simulation tools.

Thus, the proposed approach solves the problem of qualimetric integrated assessment in the system of control and decision making in a complex system in the conditions of digital transformation of business processes of the mining industry. Qualimetric support of ore-stream is provided by technological tools, such as remoteness of control and measurement operations [11].

The organizational structure contains: literature review of formal methods and models of risk assessment in management and control systems; problem; research methods; theoretical research results; computer modeling; conclusions.

## II. Literature Review of Formal Methods and Models for Risk Assessment in Management and Control Systems

In classical and modern management science, it is believed that the management system is based on four functions: organization, planning, motivation and control [1]. Control is present to varying degrees in all management functions, but is often identified as a separate organizational or technological system agent. The process of control by the organizational and technical system contains the following sequence of operations: measurement; comparison of the measured value with the norm; analysis of the result; decision making [2,3,4]. The main focus of these papers is on the quantification of control errors (control risks), which are functions of statistical properties and characteristics of the agents of the control system. Statistical properties are understood as distribution laws, and most of the works investigated three laws: the normal law of distribution of a random variable (Gauss's law), Weibull's law, and the equal probability law [5,6]. The papers investigated the influence of the shape of statistical laws of distribution of controlled parameters on probable errors (risks) of control. At the same time, all researches propose different initial constraints, hypotheses and statistical conditions. Initial constraints include their form, e.g.: lower constraint norm, when the controlled indicator must be above the limit $S>S_l$; upper constraint norm, when the controlled indicator must not exceed the value $S<S_u$; tolerance constraint $S_l<S<S_u$. At each constraint, compositions of distribution laws of the controlled parameter and measurement error were investigated.

Under the probability of undetected reject $P_{ur}$ is considered the case when the true value of the controlled parameter is outside the permissible limits, and the control system registers this fact as the presence of the parameter in the permissible zone. And vice versa, when the controlled parameter is in the tolerance zone, and the control system registers this fact as a parameter out of the tolerance zone with probability $P_{fr}$. The hypothesis of distribution of the controlled parameter and measurement error according to the Gauss law has been investigated in known works [7].

Some of the papers investigate the hypothesis of distribution of the controlled parameter according to the Weibull law, and of the measurement error according to the Gauss law. Using the integral function of the Weibull law, the expressions for calculating the probabilities of false reject - $P_{fr,}$ and the probability of undetected reject - $R_{ur}$ in the following form [7,8]:

$$P_{fr}=\sum_{i=1}^{k}\left(e^{-\frac{S_i^{\beta}}{\alpha}}-e^{-\frac{S_{i+1}^{\beta}}{\alpha}}\right)\times\left[\frac{1}{\sigma_y\sqrt{2\pi}}\int_{S_l}^{S_i-3\sigma_y}e^{\frac{y^2}{2}}dy+\frac{1}{\sigma_y\sqrt{2\pi}}\int_{S_u}^{S_i+3\sigma_y}e^{\frac{y^2}{2}}dy\right]$$

$$P_{ur}=\sum_{i=1}^{k}\left(e^{-\frac{S_i^{\beta}}{\alpha}}e^{-\frac{S_{i+1}^{\beta}}{\alpha}}\right)\frac{1}{\sigma_y\sqrt{2\pi}}\int_{S_l}^{S_i-3\sigma_y}e^{\frac{y^2}{2\sigma_y^2}}dy\times\sum_{i=1}^{k}\left(e^{-\frac{S_i^{\beta}}{\alpha}}e^{-\frac{S_{i+1}^{\beta}}{\alpha}}\right)\frac{1}{\sigma_y\sqrt{2\pi}}\int_{S_u}^{S_i+3\sigma_y}e^{-\frac{y^2}{2\sigma_y^2}}dy, \quad (1)$$

Analyzing the nature of risk in an environment of parametric fuzziness and data uncertainty showed that risk represents some virtual space or augmented reality phenomenon. According to current digital understandings, this virtual environment is part of a "meta-universe". The "meta-universe", as noted in publications, is "far from being a new term" [9]. The first concepts of the meta-universe had only fantastical outlines related to travelling beyond the galaxy. It represents something between the real and fictional worlds. Nowadays, the concept of "meta-universe" has started to acquire practical contours and penetrate into many spheres of life, such as: social networks, real estate sector, investments, working sphere, augmented reality, cryptocurrency world, online games, etc. The challenge is to "look at life beyond the boundaries of conventional understanding", which ultimately offers and generates the "digital transformation" of the risk management process. Nowadays, risk is an integral part of human "digital" life and is present in virtual and real forms of being, largely determining the "quality of life" at all stages of the "life cycle" of an object [10].

## III. The Problem

The main problem is to quantitatively assess ore quality under production conditions while minimizing technological costs. The research is carried out on the example of quality control of iron-containing ore material at the final stage of technological preparation of ore for smelting. At this stage, the tasks of estimating the percentage content of the useful component in the ore mass and building an optimal technological model that ensures minimum risks of ore quality control and subsequent economic losses are solved.

## IV. Research Methods

The research methodology is based on the system approach. In this interpretation, the system is considered as an integrated set of controlling digital agents of a multi-parameter technical and economic system. The key agent in quality management of the object under research - ore flow - is considered to be the process of control and risks regulated by IEC 31010 standard. For the optimal solution of the problem, formal methods of description of production and technological processes in the environment of digital transformation of management are used. The formalization of solved problems relies on the following mathematical tools: probabilistic and simulation models, fuzzy sets, agent-based approaches, expert evaluations. The software application developed in previous researches is used to conduct the computer experiment. Statistical data for modelling are used

from the reporting documents of sectoral enterprises. Fisher's F-criterion and Student's t-criterion were used to examine the statistical material for homogeneity. Statistica 10 package was used to process the results of statistical research.

## V. Results of Theoretical Researches

### A. Virtual Paradigm of Ore-Stream Quality Control in the Environment of Digital Transformation of Mining Economy

To achieve the goal in the scope of the proposed research the following tasks are solved: development of organizational and technological model of remote control of ore mass quality; optimization of technical and economic indicators of agents of remote control of ore quality; development of formal model of quantitative assessment of control risks in the ore-stream quality management system.

The real physical model of spatial iron concentration distribution in the ore yard area is of random nature. It is technically and technologically impossible to carry out direct control and measurement operations in different points of the "ore yard" area of 100x900 m. in the real environment. Therefore, this research proposes the use of unmanned aerial vehicles equipped with the necessary sensors, technical means of control and communication with a stationary local center for processing current on-board information (DPC) (Fig. 1). The number of control points is measured by the ratio S/Δ, where: S=L*M; L-length of the ore yard; M-width of the ore yard, S-area of the ore yard, Δ-distance between control points.

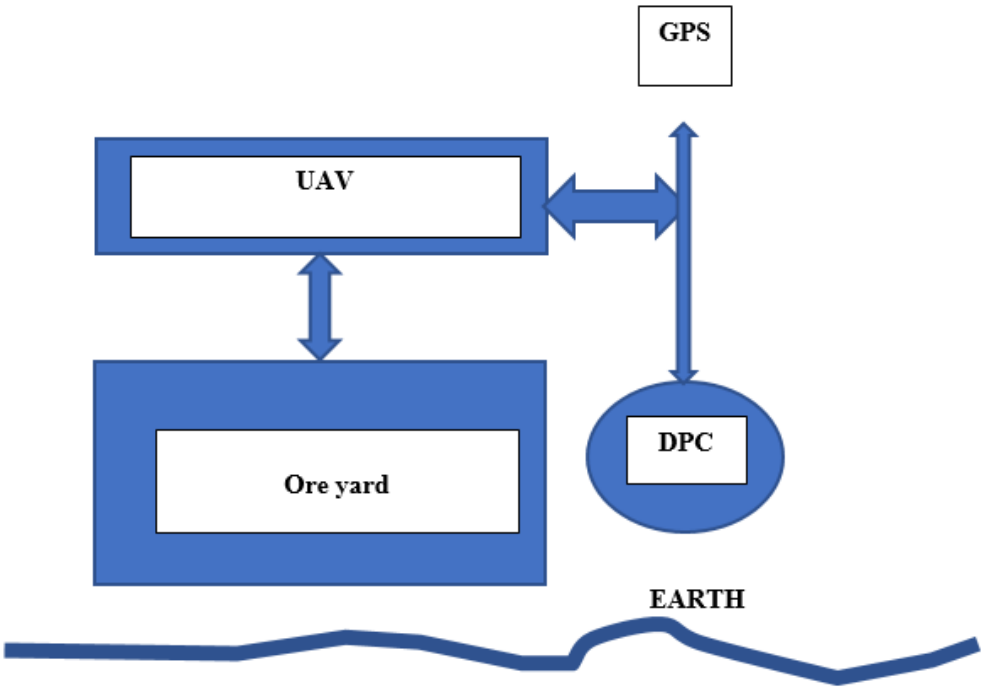


Fig. 1. Functional-technological model of the system for remote monitoring of iron ore quality.

The use of an unmanned vehicle significantly simplifies control and measurement operations, increases the manufacturability of control, but increases the cost of the project [11]. The proposed technological model transforms the continuous magnetic field of the ore yard into a digital controlled equivalent. The array of control and measurement information will be represented by a virtual digital spatial-information digital field (model), which is shown in Fig. 2.

| | | | |
|---|---|---|---|
| $\{H_{n,1}\}$ | $\{H_{n,2}\}$ | …….. | $\{H_{n,m}\}$ |
| ……. | …… | …….. | ……. |
| …….. | ……. | ……. | …… |
| …….. | ……. | ……. | …… |
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| …… | ……. | …….. | …… |
| ……. | …….. | ……. | ……. |
| $\{H_{1,1}\}$ | $\{H_{1,2}\}$ | …….. | $\{H_{1,m}\}$ |

Fig. 2. Digital 2D model of magnetic field strength values in the ore yard area.

Each element of the information array contains the result of measuring a separate digital equivalent of the magnetic field values $H_{ij}$ in some coordinate $x_{ij}$ of the ore yard surface. The array size is determined by the requirements to the control accuracy, which depends on the number of elements on the digital field area. The total number of digital $H_{ij}$ on the area of the ore yard (field) is determined from the expression N=M*L/Δ. Sampling intervals Δ can be set manually by the operator. The maximum value of the sampling parameters is determined by the positioning accuracy of the unmanned vehicle.

### B. Optimisation of Technical and Economic Indicators of ore-stream Quality Control Agents

The final practical result of this research is software applications, the use of which allows quantitative assessment of producer risks and consumer risks in probabilistic form. It is also presented the possibility of assessing the reliability of control under given statistical laws and characteristics of random

control agents. As it was established, control risks are functions of statistical parameters. Having preliminary or reported experimental material in a particular practical project, it is possible to solve the control problem in an optimal way under given metrological and resource limitations at the initial stage of work. It is also possible to solve the reverse problem, when metrological indicators of the used system support are specified and quantitatively known, and also norms and regulations are specified, then it is possible to quantitatively predict the quality of control by the sought indicators of reliability and risks. Quantitative values of producer and consumer risks have limited economic or social potential. Each investment project or business plan is completed with specific financial estimates, usually in monetary terms. Such a problem with specific economic calculations acquires an econometric form. In this paper the term 'econometrics' is interpreted as "Econometrics is one of the most effective controlling tools". In some economic literature this term is given a more extended interpretation: "Statistical analysis of economic data is called econometrics, which literally means: the science of economic measurement" [12]. The use of econometric approaches to the proposed subject study opens up the possibility of optimizing the metrological indicators of the ore-stream quality control system. In similar problems, which were solved by a number of researchers in the field of technical diagnostics, the following logic of analysis was proposed [7]:

- Control and measurement works require certain costs for instrumentation (instruments), premises, consumables, staff salaries, computer equipment, etc.
- The cost of metrological support depends on the accuracy of measurements, as established in practice, in an exponential way.
- As measurements become more accurate, the lower the risks of control, and the subsequent economic losses associated with the risks.

This approach has the following graphical interpretation (Fig. 3) [4,5,16].

The main labor intensity in the implementation of such an approach to the optimal solution of the problem on the example of ore-stream quality control in real conditions consists in the organization and carrying out of experimental and statistical researches and further empirical formalization of integral and element-by-element economic costs and predicted benefits in quantitative measurement. In analytical form, the graphical model (Fig. 3) will have the following interpretation:

$$Ctot = Ccosts + Closses , \quad (2)$$

Ccosts costs include: the cost of the quadrocopter with the Cqu hanging tool, the cost of the magnetometer Cmag, the cost of the digital control system Cc, the cost of the maintenance system Cm, the cost of in-house technical staff Ci, and the cost of the software Cs.

A significant part of the total costs is the price of the quadrocopter together with the equipment and technical support of the entire unmanned system. Research and analysis of the UAV market by criteria of cost, reliability, operational and target efficiency showed that the market offers a very large price range of UAVs adapted for various industrial and scientific purposes.

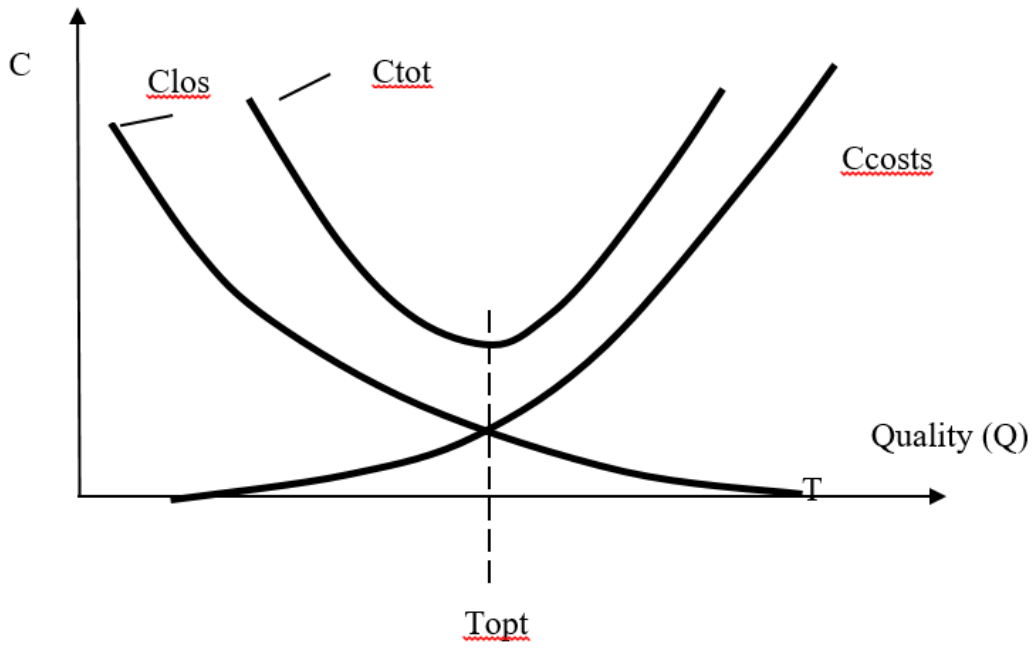


Fig. 3. Graphical model of risk optimization as a function of control accuracy [7]. C - costs; Ctot - total costs; Clos - losses from the reduction of control accuracy; Ccosts - costs of acquisition and operation of control and measuring equipment; T - control accuracy; Topt - optimal accuracy.

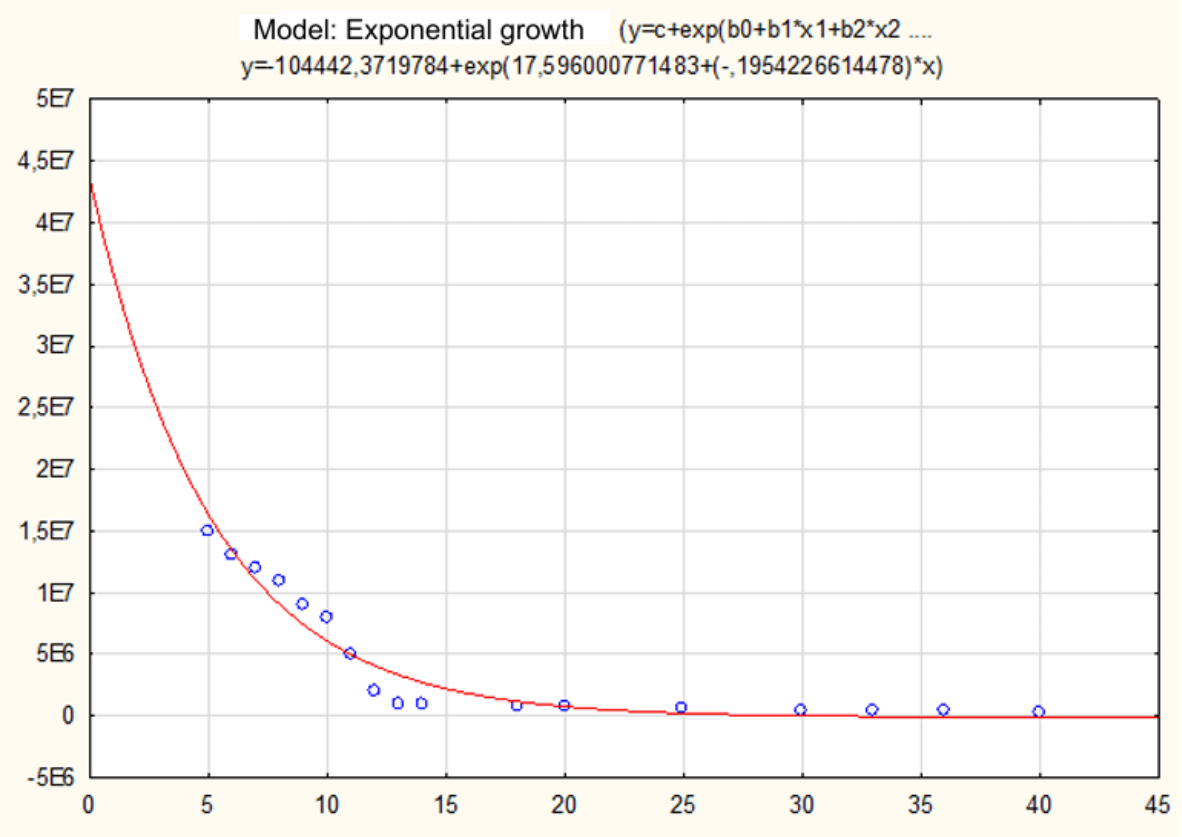


Fig. 4. Cost of tools and software in the ore-stream quality control and monitoring system.

An important economic component in the total production costs is the cost of the measuring complex, which includes: the cost of the magnetometer, the cost of premises for maintenance of the unmanned system, the cost of instrumental and information-measuring support for maintaining the operational reliability of the entire ore-stream quality monitoring system, the cost of maintenance personnel. As follows from the materials presented above, control risks and losses in the function of risk level are closely related to metrological indicators of the control and decision-making process at all stages of the life cycle of the system under research. According to the results of the analysis of Internet resources, literature sources, scientific and technical reports, the statistical material on this problem was collected, which after preliminary processing in the graphical design has the following form (Fig. 4):

The regression empirical approximation of the graphical model is as follows:

$$Ccosts = 104442{,}37+\exp(17.6-0.195V, \quad (3)$$

where V is the relative uncertainty of the control in percent (V= σl/Have, %).

In this model, the explained proportion of variance is 0.940, correlation coefficient R = 0.969, F=12.6.

The second component of expression (1) Closses quantifies the probable losses incurred by the business from emerging control risks in the digital control system in the form: Pfr - probability of producer risk and Pur - probability of consumer risk. Quantitative digital risk assessments can be referred to as virtual or augmented reality assessments. Giving these assessments a quantitative measurable economic content is one of the tasks in the ore-stream quality control system. The methodology of formal description of many technological processes and economic evaluation of losses at each of the process stages is an extremely difficult task in digital object control, since each agent of the investigated process is a “black box”.

### *C. Development of a Precedent Model for Control Risk Assessment in Technology to Improve the Homogeneity and Averaging of Ore Material*

One of the labour-intensive process steps in metallurgy is ore averaging [13]. Ore averaging seems to be a very necessary technological process due to the fact that ore from different deposits is a multicomponent and dissimilar mineral structure. Process regulations for ore smelting are oriented towards a product with a certain tolerance percentage of a useful component, such as iron, in the range Femin to Femax, which corresponds to a magnetic field value in the range Hmin to Hmax. Ore transported from the mines is unloaded to the “ore yard” in layers and stacks in a certain order. The ore is taken by the excavator across the layers so that the grab grabs as many layers as possible at the same time, and already at this technological stage the ore shipped from the ore yard is averaged. On average, the stack capacity is 100 thousand tonnes

and the number of layers is in the range of 300-1000. The magnetic field Hi(x,y) is monitored over the entire area with a certain metric step Δx;Δy. Two-dimensional address point H(i,j) is a spatial coordinate of a virtual area of L×M size. The number of information addresses is determined by the technical and technological capabilities of the magnetometer and UAV. The data information matrix will look as shown in Fig. 2. The accuracy of control is determined by the metrological indicators of the remote control system, which also includes the accuracy of UAV positioning and variability of the controlled parameter. The quality of homogeneity of the controlled ore environment in the operating mode is assessed operationally in the round-the-clock mode according to the established technological regulations with specified time intervals between control sessions. As noted above, most of the works consider modelling options where it was assumed that norms are deterministic values. Practice shows that this hypothesis simplifies the situation, which leads to significant methodological errors. This implies the necessity of building formal models taking into account the uncertainty of norms, which seems to be a precedent approach [14,15].

Considering the control system as a "black box", norms should be considered as one of the components of this precedent system, which has a high degree of uncertainty. The statistical nature of norms, as an objective fact, has been considered in many works [5,6,7,8]. As a measurement error in these works it is proposed to use the value of uncertainty, which is quantified by the mean square deviation [16,17]. Uncertainty among the key factors of control and decision-making risks in the system of precedent management should be considered as a phenomenon and as a consequence of incomplete knowledge about the topic under study, i.e. as a factor of "black box", a factor of environmental influences, unclear or inadequate understanding of objectives. The technical field has its own specificity and traditions, where the priority is given to instrumental metrology and, first of all, to measurement errors in the control system.

In the proposed research, priority in the ore-stream quality management system is also given to the uncertainty of norms, which are considered in formal models as random variables having different distribution laws. Possible management risks are investigated in the pre-project stages, and subsequently at some stages of the life cycle as required. As a rule, risk research is carried out in many practices at a qualitative level. However, in production reality, economic and other projected losses are of practical value only if they are quantified.

From all the above theoretical and practical material, in relation to the subject area under study, there arises the need and the task of quantifying the impact of the statistical nature of the tolerance field on the quality of control, and as a consequence on the quality of the ore-stream control system, under conditions of statistical uncertainty of agents and control precedents [18].

Without giving intermediate conclusions, the probable number of objects erroneously rejected from the whole sample N is expressed by the following formula [5]

$$N_{fr} = \sum_{i=0}^{m} N \int_{Li}^{Hi} \theta(Bl)dBl \left[ \sum_{j=0}^{k} \frac{1}{\sqrt{2\pi}} \int_{\theta_i}^{\lambda_i} e^{-\frac{t^2}{2}} dt \times \frac{1}{\sqrt{2\pi}} \int_{\frac{3j}{k}}^{3} e^{-\frac{z^2}{2}} dt \right], \quad (3)$$

The likely number of undetected reject results will be:

$$N_{ur} = \sum_{i=0}^{m} N \int_{Li}^{Hi} \theta(B)dB \left[ \sum_{j=0}^{k} \frac{1}{\sqrt{2\pi}} \int_{\theta_i}^{\lambda_i} e^{-\frac{t^2}{2}} dt \times \frac{1}{\sqrt{2\pi}} \int_{\frac{3j}{k}}^{3} e^{-\frac{z^2}{2}} dt \right], \quad (4)$$

where the distribution density function of the normative value of the controlled parameter B has the following form and parameters:

$$\theta(Bl) = \frac{1}{\sqrt{2\pi} \cdot 6n} e^{-\frac{(Sn-Sal)^2}{62_n}}$$

Ϭn - standard deviation of the distribution density function of the normative value of the controlled parameter B;

Sal - arithmetic mean of the lower norm of the controlled parameter B.

Expressions (3-4) presented in such a probabilistic form have an extremely complex analytical structure, which will lead to a very high methodological error in numerical computer implementation. Therefore, the use of simulation modelling [19,20,21] is evidently recommended in the problems of this subject matter. With this in mind, a simulation model is developed and proposed in this research, the algorithm of which is shown in Fig. 5.

The logic and operation of the algorithm can be clearly read and understood from the functions of each of the model blocks. The work of the algorithm starts with the input of statistical model data: $H_{ave};\sigma_u;\sigma_{meas};\sigma_l,\sigma_u;H_{lave},H_{uave}$. The optimal number of simulation cycles is found experimentally. The simulation is completed by outputting the values of risk and control reliability

$$P_{fr} = N_{fr}/M \text{ and } P_{ur} = N_{ur}/M,$$

Headings, or heads, are organizational devices that guide the reader through your paper. Where $N_{fr}$ is the content of the false reject counter; $N_{ur}$ is the content of the undetected reject counter; M is the total number of simulation tests.

The reliability D is calculated using the formula $D = 1 - (R_{fr} + R_{ur})$.

A software application has been developed for quantitative calculations of control risks by computer modelling. Making quantitative simulation calculations at different compositions of statistical laws of distribution, it is possible to find out the degree of influence of forms of statistical distributions on the result, which will determine the scope of experimental research and the final reliability of the results. The final stage in the quantitative assessment of risks is to give them a quantitative economic content, which is discussed above.

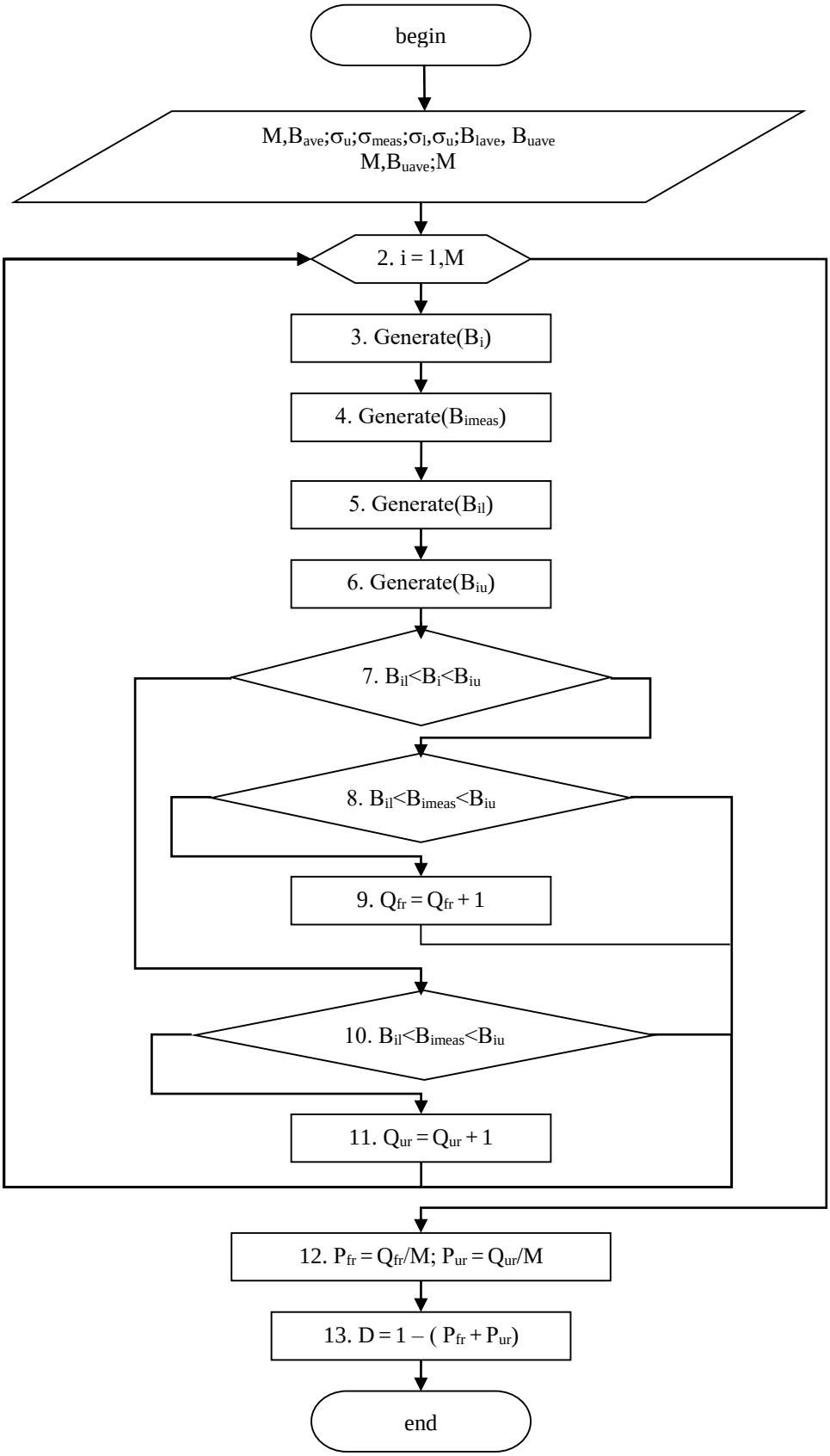


Fig. 5. Algorithm of simulation model for quantitative assessment of control risks under uncertainty of normative values.

## VI. Computer Modelling

The software application [21] was used for computer modelling in order to obtain the calculated risk values for the ore consumer. The results of computer calculation of probable risks of $P_{ur}$ control, under non-deterministic regulations are given in Table I.

$P_{ur}$ control errors in commercial settlements between the producer and the consumer of ore depend on a variety of market factors. These factors include exchange prices for ore of a certain quality. Ore quality is primarily determined by the percentage iron content. It is common practice at the iron ore exchange to ration ore into three qualities levels - 40%, 50%, 60%. Ore of high quality (60%) may be quoted under separate situational rules with a high level of uncertainty.

To visualize the process of modelling data analysis, using expression 3, a 3D model of total costs in the ore-stream quality control system was built using $P_{ur}$ risk as an example. The 3D modelling results are presented in Fig. 6.

As it follows from Fig. 6, the three-dimensional surface of total costs of Var3 in the system of risk management and quality control of ore-stream shows a clearly expressed area of minimum, which corresponds to the norm of iron content in ore material equal to 40%.

To quantitatively analyze the results of modelling, the total present value of probable monetary losses of the ore consumer as a function of control errors $P_{ur}$ was estimated for the norm 40% and ore volume: V=1000000 t (cost Cdol/t=100) (Table II).

TABLE I. Result of Computer Modelling of Probable Control Risks $P_{UR}$ (Ore Consumer Risk)

| Technological rule of average iron content according to the level of magnetism in ore $H_{ave}$,% | **Relative uncertainty of ore grade control, $\sigma/H_{ave}$** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| $P_{ur}$ (%) at iron content rate $H_{ave}$>=40% | 2.1 | 3.3 | 4.5 | 12.9 | 17.15 | 20.5 | 24.0 | 28.1 | 30.2 |

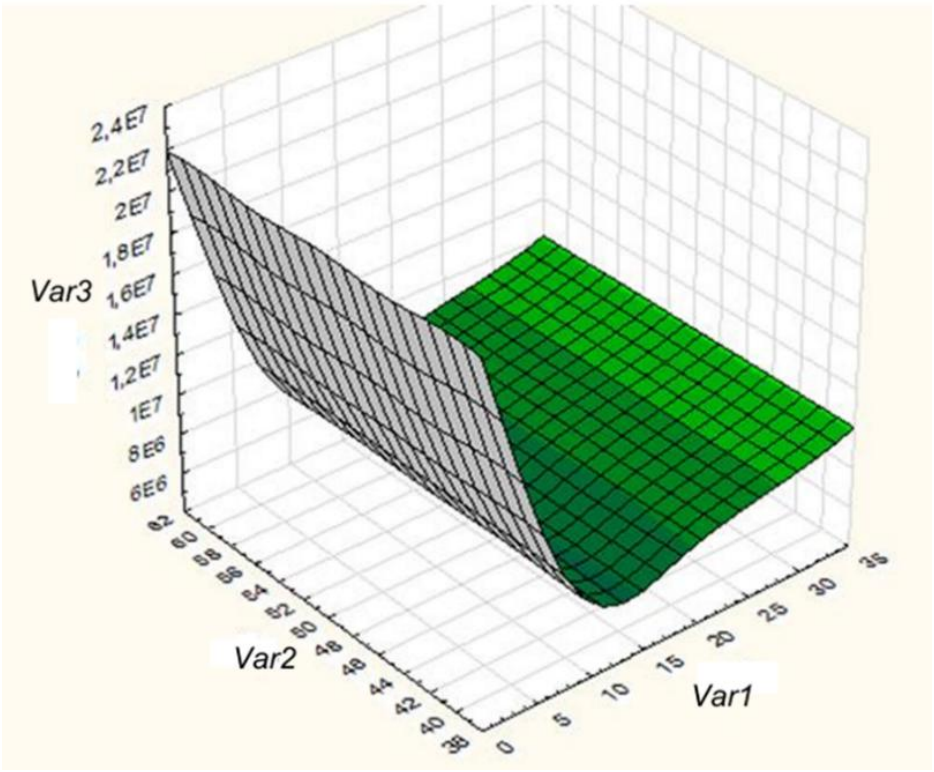


Fig. 6. Results of 3D modelling of total costs in the ore-stream quality control system. Var3 - total costs as a function of control accuracy and norms value; Var2 - norms value; Var1 - control uncertainty (accuracy).

TABLE II. Total Present Value of Probable Monetary Losses of the Ore Consumer as a Function of Control Errors $P_{UR}$ for the Norm of 40% and Ore Volume:V=1000000 Tonnes (cost Cdol/t=100)

| Average iron content rate by magnetism level in ore $H_{ave}$,% | Relative uncertainty of control ($\sigma/H_{ave}$) | | | | | |
|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 |
| $P_{ur}$ (%) at iron content rate $H_{ave}$>=40% | 15000000 | 9000000 | 5000000 | 6770000 | 7450000 | 8300000 |

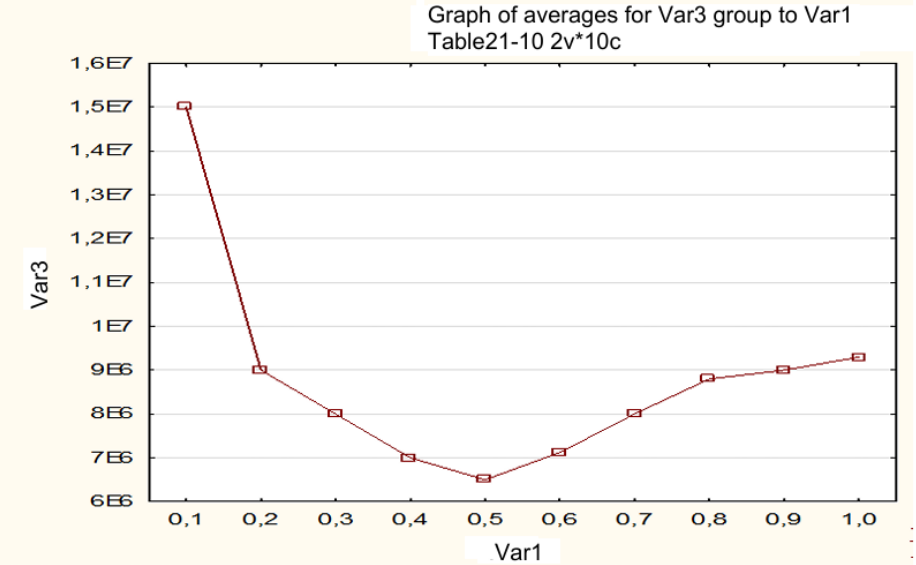


Fig. 7. Graphical 2D Model for Estimating Ore Consumer Monetary Losses as a Function of Control Errors (Consumer Risk). Var3 Financial Losses due to Probable Risk $P_{ur}$, as a Function of Relative Control Uncertainty $\sigma/H_{ave}$ (Var1) for the Norm of 40%.

Fig. 7 illustrates a graphical 2D model for estimating ore consumer monetary losses as a function of control errors (consumer risk) at a norm of 40%.

As follows from Fig. 7, the minimum of total losses in the ore-stream quality control system as a function of the accuracy of iron content control in the ore material corresponds to the ratio $\sigma/H_{ave} = 0.5$. Here $\sigma$ is the mean square deviation of the measurement error of the iron content in the ore material, and $H_{ave}$ is the average value of the controlled magnetic field strength of the ore material with a norm of 40%.

## VII. Conclusion

According to the modelling results, it was found that the ore-stream quality management system is a multifactorial process in which the key function is control. The total costs of ensuring effective digital control contain: purchase and maintenance of instrumental means of measurement; losses in the function of control quality assessed by control risks. The total cost of ensuring effective digital control has a close correlation with control and measurement risks, which determine economic losses in the ore-stream management system. Adequate assessment and forecasting of risks, as well as economic consequences of control is possible through mathematical modelling based on the data of experimental and statistical researches.

As a result of experimental researches and computer modelling, the optimal ratio of the cost of control and measuring equipment depending on metrological indicators, normative regulations for the initial ore material and statistical properties of the controlled ore material was revealed.

In the conditions of competition, developed inter-corporate and international relations and a number of other factors, an objective quantitative assessment of the economic efficiency of new innovation projects in practice seems possible with a formalized quantitative calculation of total costs and losses as a function of the accuracy of control and decision-making.

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# Detection and Classification of Intestinal Parasites with Bayesian-Optimized Model

Haifa Hamza[1]*, Kamarul Hawari Ghazali[2]*, Abubakar Ahmad[3]
Faculty of Electrical Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, 26600 Pekan, Pahang, Malaysia[1, 2]
Faculty of Computing, Universiti Malaysia Pahang Al-Sultan Abdullah, 26600 Pekan, Pahang, Malaysia[3]

***Abstract*—Automated detection of intestinal parasites in medical imaging enhances diagnostic efficiency and reduces human error. This study evaluates object detection techniques using Faster R-CNN with different backbone architectures such as ResNet, RetinaNet, ResNext and YOLOv8 series for detecting *Ascaris lumbricoides* and *Trichuris trichiura* in microscopic images. A dataset of 2000 images was split into training (1500), validation (300), and testing (200). Results show Faster R-CNN with RetinaNet achieves the highest Average Precision (AP) across varying Intersection over Union (IoU) thresholds, making it robust in feature extraction. However, YOLOv8 excels in real-time detection, with YOLOv8n (nano) providing the best trade-off between accuracy and computational efficiency. Bayesian Optimization further improves YOLOv8n, achieving an AP of 99.6% and an Average Recall (AR) of 99.7%, surpassing two-stage architectures. This study highlights the potential of deep learning for automated parasite detection, reducing reliance on manual microscopy. Future research should explore transformer-based models, self-supervised learning, and mobile deployment for real-world clinical applications.**

***Keywords*—Intestinal parasites; faster region convolutional neural network; You Look Only Once (YOLOv8); Bayesian Optimization; medical imaging; object detection**

## I. Introduction

Intestinal parasitic infections significantly impact global public health, particularly in low-resource and developing regions [1]. Among the most prevalent species are *Ascaris lumbricoides* and *Trichuris trichiura*, which together infect hundreds of millions of individuals worldwide and contribute to malnutrition, cognitive impairments, and socioeconomic challenges [2], [3]. Accurate and timely diagnosis of these infections is essential for effective treatment, surveillance, and public health intervention strategies. Traditional diagnosis via manual microscopic examination, although widely used, is fraught with limitations such as labor intensiveness, inter-observer variability, and significant dependency on expert knowledge [4], [5]. These constraints often lead to delayed diagnoses or misclassification, undermining effective disease control. As such, there is a pressing need for automated, robust, and scalable diagnostic tools that can reliably identify parasite eggs across varying image conditions.

Recent advancements in machine learning (ML) and deep learning (DL) have demonstrated promising capabilities in automating visual diagnostic tasks. However, ML techniques frequently rely on handcrafted features and struggle with image variability and segmentation challenges. Meanwhile, DL approaches such as CNNs and U-Nets offer improved performance through hierarchical feature extraction, demanding substantial computational resources and large annotated datasets. These resources are often unavailable in the very settings most affected by parasitic diseases [6].

### A. Research Problem and Objectives

The central research problem is the lack of real-time, high-accuracy parasite detection tools suitable for resource-constrained clinical settings. Existing models either compromise on computational efficiency or fall short on precision in complex image environments [7]. This study aims to overcome this limitation by identifying and optimizing an object detection architecture that provides a reliable trade-off between accuracy and processing speed.

This research addresses these challenges by proposing a novel, optimized diagnostic solution based on the YOLOv8n model, which is a part of a single-stage object detection framework known for real-time efficiency and accuracy. The core innovation lies in using Bayesian Optimization to fine-tune YOLOv8n's hyperparameters, enabling the model to deliver state-of-the-art accuracy (AP of 99.6%) and recall (AR of 99.7%) with minimal computational overhead.

The study begins with a literature review covering traditional ML and recent DL techniques in parasite detection, highlighting their respective strengths and shortcomings. The methodology section details the dataset, model architecture, and evaluation metrics used in the study. Results are presented comparing various model performances, with a particular focus on the improved YOLOv8n model. Finally, the discussion emphasizes the practical implications of the findings and proposes directions for future research, including the integration of transformer models and mobile deployment

### B. Significance and Contributions

This work makes significant contributions to the field of biomedical imaging and parasitology by:

- Systematically comparing both two-stage (Faster R- NN) and single-stage (YOLOv8 series) object detection models across standard benchmarks.
- Demonstrating the superior performance of YOLOv8n for real-time detection in low-resource settings.

- Introducing a Bayesian Optimization framework that enhances the model's performance through intelligent hyperparameter tuning.
- Presenting a detection pipeline that can feasibly be deployed in clinical workflows, thereby reducing diagnostic delays and improving healthcare outcomes.

The findings contribute to advancing automated parasite detection, paving the way for real-time, scalable, and resource-efficient diagnostic solutions in medical and environmental applications.

## II. Literature Review

### A. Machine Learning

Machine learning techniques have been instrumental in solving some of the challenges in detecting and classifying intestinal parasites. These include Support Vector Machines, BoVW, and Laplacian SVM, among others, which have achieved success in automating parasite classification, enhancing energy efficiency, and solving the out-of-distribution problem in parasite-egg detection [8], [9], [10], [11]. The combination of BoVW with SVM achieved considerable accuracy on classification for various reptilian parasites from stool images, whereas SoftMax thresholds are used for feature selection to deal effectively with out-of-distribution (OO-Do detection).

Most of the ML methods inherently suffer from issues of limited labelled data, manually crafted feature extraction, and dealing with high-dimensional image data despite their successful performance; hence, there is an ever-rising need to develop an automatic feature-learning technique and handle variability in image quality.

Besides, many of these ML models suffer in general from the problem of segmentation, which makes them easily lose their performance on new unseen datasets, and was presented in [9] by Ren et al. The work has thus recently shifted more toward deep learning methods because they have been seen to have the capabilities for high-level feature learning; in addition, deeper learning will be able to capture and model more complex image information data, hence overcoming so much weaknesses related to more conventional ML techniques.

### B. Deep Learning

Deep learning emerged as a revolutionary methodology to solve complex problems in the detection, classification, and segmentation of parasites. Models with CNNs, YOLO architectures, and transfer learning strategies have delivered exceptional performance in application scenarios that demand high accuracy and automated feature extraction. For instance, YOLOv5, CNN, have achieved considerable success in the detection of protozoan cysts and helminth eggs and malaria parasites with accuracies mostly greater than 95% in [12], [13]. Besides, deep learning models like U-Net have achieved detection accuracies as high as 99.8% in detecting human intestinal parasites [14].

However, this is not to say that there are no limitations in deep learning. In particular, these include dependencies on large and diverse datasets, high computational costs, and sensitivity to variations in image quality. Suwannaphong et al., in [15], for instance, recorded a drop in performance upon using low-resolution images from USB microscopes. In addition, some approaches cannot classify morphologically similar types of parasites easily [16]. Some challenges identified include: integrating clinical real-world data sets, improving model architectural robustness, and employing hybrid models to leverage strengths from the different machine learning and deep learning models.

In this work, efforts are made in optimisation of models for resource-constrained settings to enhance generalisability to unseen data. Transfer learning is a method in which pre-trained models are used, especially with small-sized datasets, in order to perform better. For parasite detection, this technique has often been used due to its limited and low-quality dataset [17]. Therefore, transfer learning leverage knowledge from larger and higher quality datasets to enhance feature selection with much better accuracy. Several works, such as [18] and [15], have shown success in using transfer learning methods to improve the accuracy of parasite detection models.

### C. Hybrid and Ensemble Learning

Some intractable problems in parasite detection are being tried to be overcome by the hybrid and ensemble learning methods combining the powers of ML and DL. Among these techniques, some methods like VGG16 along with SVM and some ensemble approaches, such as ResNet50 with DenseNet201, have outperformed all previous works related to intestinal and blood parasite classification. For example, Bhuiyan and Islam in [19], reported 97.92% accuracy using a hybrid model for detecting protozoa and helminth eggs. Ensembles of CNNs and traditional ML classifiers have also performed well in addressing variability in feature extraction and boosting the accuracy over multi-class tasks in works such as [20] and [21].

Although ensemble methods tend to give higher accuracy, there is usually an added problem of computational complexity and high training times, a process that was noted by Butploy et al. in [22]. Therefore, hybrid models are computationally expensive and in some cases constitute a major source of concern, especially within resource-poor clinical areas.

These challenges further raise the need for refined research on ensemble methods to reduce computational demands and involve sophisticated optimization techniques, such as quantum learning or lightweight models. This analysis underlines the movement from traditional ML techniques to advanced DL and hybrid methods. This reflects the unruffled effort that has gone into overcoming the challenges of parasite detection to improve upon the accuracy, efficiency, and scalability of the approach.

## III. Methodology

The methodology outlines the systematic approach undertaken to evaluate the performance of state-of-the-art object detection models in detecting intestinal parasites. This section describes the dataset, the preprocessing steps employed, the models used, and the evaluation metrics applied. The goal is to assess and compare the effectiveness of the models in classifying and detecting two classes of parasites, *Ascaris*

*lumbricoides* and *Trichuris trichiura*, using robust and reproducible experimental protocols.

### A. Dataset Description

A dataset of 2000 microscopic images was used, comprising two classes of intestinal parasites: *Ascaris lumbricoides* and *Trichuris trichiura*. The dataset was divided into; 1500 images as training set, 300 images as validation set and 200 images as testing set. Each image was pre-processed to ensure uniform dimensions and enhanced contrast for optimal model input.

### B. Models Evaluated

This research attempts to optimize the best-performing models among the established baseline models. Object detection for parasite identification, specifically *Ascaris lumbricoides* and *Trichuris trichiura*, requires a balance between detection accuracy and inference speed. Object detection architectures fall into two categories: two-stage and single-stage models. Two-stage architectures, such as Faster R-CNN (FRCNN), excel in precision but often suffer from higher computational costs. Conversely, single-stage architectures, such as the YOLOv8 series, prioritize real-time detection with competitive accuracy. Ensemble learning leverages multiple models trained on the same dataset, combining their predictions to enhance precision and reduce variability. The individual models trained include:

*1) Two-Stage architectures:* Faster R-CNN (FRCNN) is a well-established two-stage detection framework that provides high detection accuracy by first generating region proposals and then refining predictions. To enhance performance, several backbone architectures and frameworks have been integrated with FRCNN:

*a) Faster RCNN with ResNet Backbone:* Utilizes ResNet for feature extraction, known for its accuracy and efficiency in hierarchical feature learning. Both ResNet_50_FPN and ResNet_101_FPN were used in the experiment.

*b) Faster RCNN with RetinaNet Backbone:* Incorporates RetinaNet's focal loss function to address class imbalance, ensuring precise detection of small and irregularly shaped objects.

*c) FRCNN with ResNeXt backbone:* ResNeXt's grouped convolution structure was used to improve feature representation and classification.

These configurations provide robust detection performance but may introduce computational overhead, limiting real-time applications in field environments.

*2) Single-Stage architecture:* The YOLOv8 series offers a single-stage alternative with five model sizes: YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large) and YOLOv8x (extra-large), balancing accuracy and efficiency. Single-stage models eliminate the region proposal step, allowing for faster inference while maintaining high detection precision. In this study, YOLOv8n performed better than other variants with the parasite datasets used for this study. The optimal trade-off between speed and accuracy, made it even more suitable for real-time parasite detection with limited hardware resources. YOLOv8n's advantages include:

- Efficient feature extraction using CSPDarkNet backbone.
- Improved object localization through anchor-free detection.
- Optimized performance on edge devices for real-world applications.

The different architectures are summarized in Fig. 1.

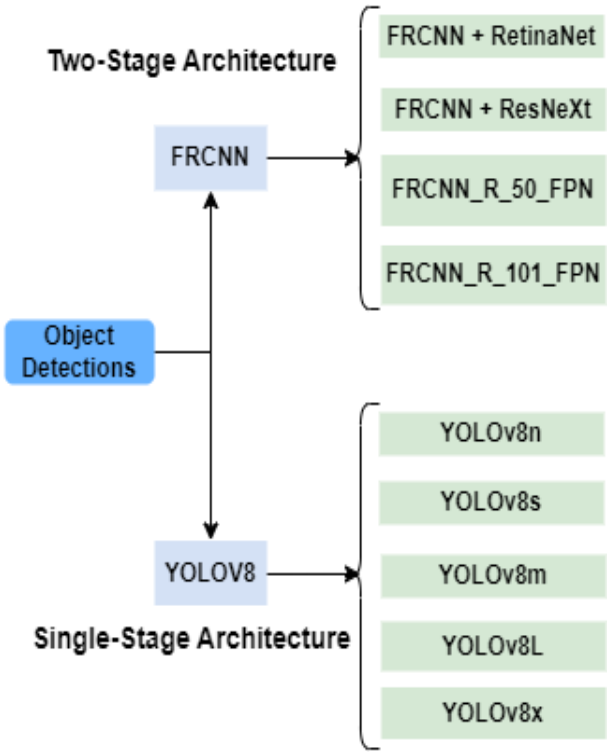


Fig. 1. The different Object detection models utilized in intestinal parasite detection and classification tasks.

*3) Selection of YOLOv8n for optimal performance:* A comprehensive evaluation was conducted by training both two-stage and single-stage object detection architectures on the same dataset to identify the most effective model for parasite detection. The two-stage Faster R-CNN (FRCNN) framework was tested with multiple backbone architectures, including ResNet_50, ResNet_101, RetinaNet and ResNeXt, each offering high detection accuracy but at the cost of increased computational complexity.

In contrast, the single-stage YOLOv8 series, comprising five model sizes (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x), provided a real-time alternative with improved inference speed and detection precision. Among these, YOLOv8n (nano) was selected as the best-performing model, offering an optimal balance between accuracy and efficiency, making it particularly well-suited for real-time parasite detection in resource-constrained environments. The results of the experiments are presented in the 'Results and Discussion' section of this study.

*4) The structure of the proposed optimized YOLOV8n:* YOLOv8 represents a significant advancement in real-time object detection, introducing a refined architectural design that enhances accuracy, efficiency, and adaptability over its predecessors. At its core (Backbone), YOLOv8 adopts a CSPDarkNet-inspired backbone, incorporating an advanced Spatial Pyramid Pooling (SPP) module and CSPLayer blocks, which improve gradient flow and reduce computational redundancy, thereby enhancing feature extraction. The core operation involves splitting feature maps and performing transformation separately before merging, as formulated in Eq. (1):

$$X' = F(X_1, \theta) \oplus X_2 \tag{1}$$

where,

- $X'$ is the input feature map, and $X_1, X_2$ are the split feature maps,
- F $(., \theta)$ represents the transformation function (e.g, convolution, activation and normalization).
- $\oplus$ denotes concatenation.

In addition, Spatial Pyramid Pooling (SPP) enhances receptive field aggregation by applying multi-scale max pooling as shown in Eq. (2):

$$SPP\ (X) = \bigoplus_{i=1}^{N} \max_{ri}(X) \tag{2}$$

where,

- N represent the number of pooling scales,
- $r_i$ denotes the pooling kernel size at scale *i*
- $\max_{ri}(.)$ applies max pooling over a region of size ri

These components collectively improve feature representation by capturing both fine and coarse-grained spatial structures.

At its neck, the model optimized Path Aggregation Network (PAN) to facilitate multi-scale feature fusion, ensuring the effective integration of fine-grained and high-level semantic information critical for detecting intricate structures such as parasites. Feature fusion in PAN is mathematically expressed in Eq. (3):

$$F_{out} = W_1 * U(F_{in}) + W_2 * D(F_{in}) \tag{3}$$

where,

- $F_{in}$ is the input feature map,
- U($U(F_{in})$ *and* $D(F_{in})$ represent up sampling and down sampling functions, respectively,
- $W_1, W_2$ are learnable weight parameters
- * denotes convolution

This hierarchical fusion ensures better retention of spatial and contextual information across different scales.

A key departure from previous YOLO variants is the introduction of an adaptive decoupled head, which independently processes classification and regression tasks, improving both localization accuracy and confidence calibration. The classification confidence score and bounding box regression are modelled as shown in Eq. (4) and Eq. (5) respectively:

- *Classification confidence*: The probability of object presence in an anchor-free paradigm is computed using a sigmoid activation in Eq. (4):

$$P(c|X) = \frac{1}{1+ e^{-z}} \tag{4}$$

where, z is the output of the classification branch before activation.

- *Bounding box regression*: The predicted bounding box coordinates (x, y, w, h) are obtained using Eq. (5):

$$\hat{x} = x_a + S_x\sigma(x) \tag{5}$$
$$\hat{y} = y_a + S_y\sigma(y)$$
$$\hat{w} = w_a e^{S_w\omega}$$
$$\hat{h} = h_a e^{S_h h}$$

where,

- $(x_a, y_a, w_a, h_a)$ are the anchor box parameters
- $\sigma(.)$ Is the sigmoid function ensuring localization stability.
- $s_x, s_y, s_w, s_h$ are scaling factors learned during training

The decoupling of classification and regression enables YOLOv8 to achieve higher precision and faster convergence compared to prior versions. Furthermore, YOLOv8 transitions to an anchor-free detection paradigm, eliminating the reliance on predefined anchor boxes that characterized earlier versions [23], [24]. This innovation streamlines the detection process, improves generalization, and reduces computational complexity, making it highly effective for parasite detection where object variability is high. The model further enhances performance through an advanced post-processing pipeline, incorporating adaptive non-maximum suppression (NMS) to minimize false positives while maintaining high recall rates.

Additionally, improved loss functions such as IoU Loss and Distribution Focal Loss (DFL) enable superior bounding box regression and confidence estimation. These advancements collectively yield a highly efficient model with reduced inference latency, making YOLOv8 particularly well-suited for real-time and resource-constrained applications in medical and biological imaging. By integrating these state-of-the-art improvements, YOLOv8 establishes itself as a robust framework for precision-driven detection tasks, offering superior speed and accuracy while preserving computational efficiency, making it an optimal choice for high-impact applications such as automated parasite detection [25].

To conclude this section, it is obvious to note that the mathematical formalization of YOLOv8's architectural components underscores its computational efficiency, multi-

scale feature aggregation, and enhanced detection accuracy. The CSPDarkNet backbone facilitates efficient feature extraction, the PAN neck strengthens multi-scale feature fusion, and the decoupled detection head optimizes classification and localization, collectively ensuring state-of-the-art performance in real-time object detection, including applications such as parasite detection in biomedical imaging.

*5) Hyperparameter tuning using Bayesian Optimization:* Bayesian Optimization (BO) has emerged as a superior hyperparameter tuning strategy for deep learning models, particularly in optimizing YOLOv8n for parasite detection, where achieving high precision with minimal computational overhead is critical. Unlike conventional grid search [26], which exhaustively evaluates all possible hyperparameter combinations, or random search [27], which blindly samples the search space, Bayesian Optimization constructs a probabilistic model of the objective function using Gaussian Processes (GPs) or Tree-structured Parzen Estimators (TPE). By iteratively refining this surrogate model and leveraging an acquisition function, such as Expected Improvement (EI), Upper Confidence Bound (UCB), or Probability of Improvement (PI)—Bayesian Optimization dynamically selects the most promising hyperparameter configurations, balancing exploration and exploitation [28].

This adaptive learning process significantly reduces the number of training iterations required to reach an optimal solution while ensuring improved detection performance. Additionally, Bayesian Optimization mitigates the inefficiencies of traditional methods by intelligently guiding the search space, preventing the combinatorial explosion characteristic of grid search and outperforming the stochastic nature of random search. This results in enhanced sample efficiency, faster convergence, and improved generalization capabilities of YOLOv8n in parasite detection tasks. By integrating Bayesian Optimization into the hyperparameter tuning process, the model achieves superior object detection accuracy with reduced computational costs, making it an ideal choice for real-time and resource-constrained applications in biomedical imaging and parasitology.

Hyperparameter optimization is a critical factor in enhancing the performance of deep learning models for parasite detection, particularly when leveraging Bayesian Optimization to refine the YOLOv8n architecture. By defining a well-structured search space, Bayesian Optimization efficiently navigates the trade-offs between convergence speed, generalization, and computational efficiency. Fig. 2 outlines the Bayesian-Optimized algorithm with YOLOv8n.

The initial learning rate (lr0), constrained within the range of 1e-4 to 1e-2 and sampled using a log-uniform prior, governs the magnitude of weight updates, ensuring a balance between rapid convergence and model stability. Momentum, ranging from 0.1 to 1.0, modulates the persistence of past gradients in stochastic gradient descent (SGD), mitigating oscillations and improving convergence stability, particularly in complex parasite detection tasks with highly variable morphological structures.

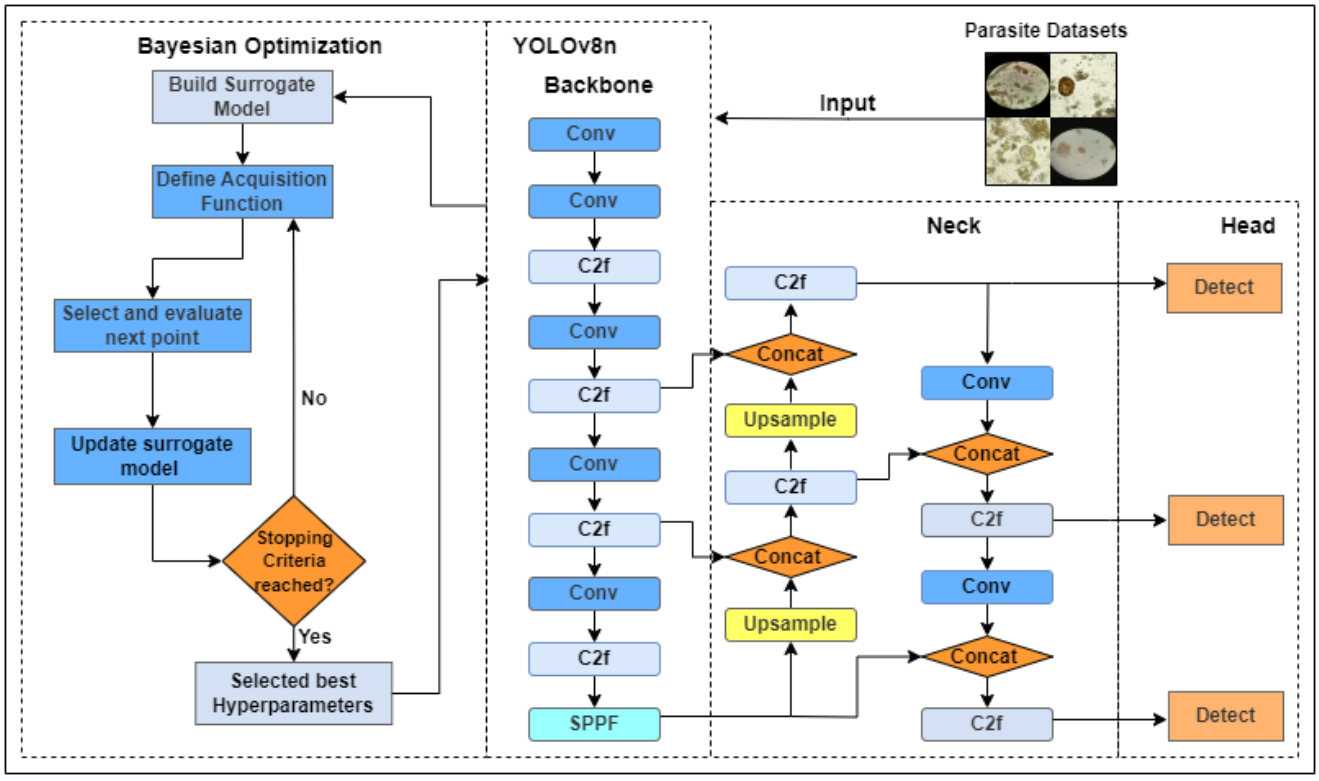


Fig. 2. Performance trends of Average Precision and Recall across varying IoU thresholds, highlighting the consistency and accuracy of detection models in intestinal parasite classification tasks.

The Weight decay (weight_decay), bounded between 0.0 and 0.0005, functions as an L2 regularization term, constraining excessive parameter growth to prevent overfitting and enhance model generalization on unseen parasitic instances. The batch size (batch), selected within the range of 4 to 32, directly impacts gradient estimation, where smaller batches offer improved generalization at the cost of higher variance, while larger batches provide smoother updates but demand greater computational resources.

Additionally, the number of training epochs (epochs), varying from 10 to 1000, determines the duration of model training, requiring careful optimization to balance learning progression with computational efficiency, thereby avoiding underfitting or excessive overfitting. By leveraging Bayesian Optimization to systematically explore these hyperparameters, YOLOv8n achieves superior detection accuracy while minimizing computational overhead, ensuring robust performance in real-time parasite detection applications.

This intelligent search process dynamically adapts hyperparameter selection based on model performance metrics such as mean Average Precision (mAP) and Intersection over Union (IoU), ultimately facilitating a highly efficient and precise detection framework tailored for biomedical imaging and parasitology research. Table I summarizes the hyperparameter ranges.

The proposed architecture for the Bayesian-Optimized YOLOv8n model is summarized in Table II and the proposed algorithm is presented in Fig. 3.

TABLE I. RANGES FOR HYPERPARAMETER TUNING

| Hyperparameter | Abbreviation | Range |
|---|---|---|
| Learning rate | lr0 | (1e-4, 1e-2) |
| Momentum | Momentum | (0.1, 1.0) |
| Weight decay | weight_decay | (0.0, 0.0005) |
| Batch size | batch | (4, 32) |
| Number of epochs | epochs | (10, 1000) |

TABLE II. THE PROPOSED ARCHITECTURE OF THE PROPOSED OPTIMIZED YOLOV8N

| Layer | Output Shape | Filter Size | Number of Filters | Stride | Padding | Activation |
|---|---|---|---|---|---|---|
| 0 | -1 | [3, 16, 3, 2] | 16 | 2 | 1 | ReLU |
| 1 | -1 | [16, 32, 3, 2] | 32 | 2 | 1 | ReLU |
| 2 | -1 | [32, 32, 1, True] | 64 | 2 | 1 | ReLU |
| 4 | -1 | [64, 64, 2, True] | 64 | 2 | 0 | ReLU |
| 5 | -1 | [64, 128, 3, 2] | 128 | 2 | 1 | ReLU |
| 6 | -1 | [128, 128, 2, True] | 128 | 2 | 0 | ReLU |
| 7 | -1 | [128, 256, 3, 2] | 256 | 2 | 1 | ReLU |
| 8 | -1 | [256, 256, 1, True] | 256 | 1 | 0 | ReLU |
| 9 | -1 | [256, 256, 5] | 256 | 1 | 2 | ReLU |
| 10 | -1 | [None, 2, 'nearest'] | - | - | - | - |
| 11 | [-1, 6] | [1] | - | - | - | - |
| 12 | -1 | [384, 128, 1] | 128 | 1 | 0 | ReLU |
| 13 | -1 | [None, 2, 'nearest'] | - | - | - | - |
| 14 | [-1, 4] | [1] | - | - | - | - |
| 15 | -1 | [192, 64, 1] | 64 | 1 | 0 | ReLU |
| 16 | -1 | [64,64,3,2] | 64 | 2 | 1 | ReLU |
| 17 | [-1,12] | [1] | - | - | - | - |
| 18 | -1 | [192,128,1] | 128 | 1 | 0 | ReLU |
| 19 | -1 | [128,128,3,2] | 128 | 2 | 1 | ReLU |
| 20 | [-1,9] | [1] | - | - | - | - |
| 21 | -1 | [384,256,1] | 256 | 1 | 0 | ReLU |
| 22 | [15,18,21] | [2, [64,128,256]] | - | - | - | - |

**Algorithm: Bayesian Optimization for YOLOv8 Hyperparameter Tuning**

***Input:*** *Pre-trained YOLOv8 model MMM, Training dataset* $D_{train}$*, validation dataset* $D_{val,}$ *Hyperparameter search space* H={$lr_0$,μ,wd,B,E}, *Number of optimization iterations* $N_{calls}$*, Random seed s for reproducibility*

***Output:*** Optimal hyperparameter set $H^*$={$lr0^*$,$\mu^*$,$wd^*$,$B^*$,E} *maximizing validation mean Average Precision (mAP@0.5).*

***Initialize Parameters:***

***Set*** $D_{train}$, $D_{val,}$ $D_{test,}$ $P_{results}$

***Set*** *experiment name* $N_{exp}$

***Load*** *pre-trained YOLOv8 model* MMM

***Define Hyperparameter Search Space***

***Define the search space*** $\mathcal{H}$ ***as follows:***

$lr_0$ ~ LogUniform ($10^{-4}$, $10^{-2}$)

M ~ Uniform (0.1, 1.0)

Wd ~ Uniform (0.0, 0.0005)

B ∈ {4,8,16,32}

E ∈ {10, 20,…, 1000}

***Define Objective Function***

*Given hyperparameter set* $\mathcal{H}_i$*, extract batch size B and number of epochs E.*

*Train the YOLO model M using:*

*Dataset:* $D_{train}$*,and* Hyperparameter $\mathcal{H}_i$

*Perform model validation on* $D_{val}$

*Compute* $mAP_{0.5}$ *(Mean Average Precision at IOU threshold 0.5)*

*Return –* $mAP_{0.5}$ *as the objective function value to minimize*

***Perform Bayesian Optimization***

***Initialize*** *Gaussian Process Optimization (GPO) with prior search space* $\mathcal{H}$

***Set*** *number of function (e.g, Expected improvement or upper confidence bound)*

***For i = 1 to*** $N_{calls}$

Sample a new hyperparameter set $\mathcal{H}_i$ from the search space

Evaluate the objective function using Steps 11-16.

Update the Gaussian Process model with new results

***end***

*Store the best hyperparameter set* $\mathcal{H}^*$

***Output Best Hyperparameters***

*Extract optimal values* $\mathcal{H}^*$={$lr_0$*,μ*,wd*,B*,E*}

*Print the best hyperparameter values found*

*Initial Learning Rate* $lr_0$*

*Momentum* $\mu$*

*Weight Decay wd**

*Batch Size B**

*Number of Epochs* E*

Fig. 3. The Proposed algorithm for the Bayesian-Optimized YOLOv8n model.

### *C. Evaluation Metrics*

The models were evaluated using the following metrics:

Average Precision (AP) at varying IoU thresholds (0.50:0.95). Measures the area under the precision-recall curve, indicating the model's accuracy in detecting objects at varying IoU thresholds as depicted in Eq. (6).

$$\text{mAP} = \frac{1}{n}\sum_{i=1}^{n} AP_i \quad (6)$$

where, AP is Average precision for class *i and*

*n* is the number of IoU thresholds evaluated (e.g., IoU = 0.5, 0.55, ..., 0.95 in 0.05 increments).

Average Recall (AR) across IoU thresholds. Represents the average recall across all IoU thresholds, reflecting the model's ability to detect true positive objects consistently as presented in Eq. (7).

$$\text{mAR} = \frac{1}{n}\sum_{k=1}^{n} AR_k \quad (7)$$

where, $R_k$ is the recall at the *k*-th IoU threshold and *n* is the number of IoU thresholds considered.

## IV. Results and Discussion

This section provides a comprehensive analysis of the performance of different object detection architectures evaluated in this study. The assessment focuses on key performance metrics, including Average Precision (AP) and Average Recall (AR) at different Intersection over Union (IoU) thresholds. By comparing the effectiveness of various detection architectures, this section highlights their respective strengths and limitations in detecting *Ascaris lumbricoides* and *Trichuris trichiura*, ultimately informing the selection of robust and scalable diagnostic models.

### A. Performance of Faster R-CNN with ResNet Backbone

The Faster R-CNN with ResNet-50 and Feature Pyramid Network (FPN) demonstrated competitive performance, achieving an AP of 85.8% at IoU 0.50:0.95, with a significant increase to 99.6% at IoU 0.50. The model maintained a relatively high AR of 99.6%, indicating strong recall capabilities in detecting true positive instances. However, a noticeable limitation was observed at stricter IoU thresholds, where precision declined, suggesting potential difficulties in accurately localizing objects at higher overlap requirements. This behaviour aligns with previous findings [29], where ResNet-based architectures prioritize robust feature extraction but may struggle in fine-grained localization due to their fixed receptive fields.

The ResNet-101 FPN variant exhibited slightly lower precision compared to ResNet-50, with an AP of 85.5% at IoU 0.50:0.95. Although it maintained a stable AR of 88.9%, it did not provide significant improvements over its shallower counterpart. The marginal performance difference suggests that deeper feature hierarchies introduced by ResNet-101 did not contribute meaningfully to detection accuracy, likely due to diminishing returns in feature extraction depth.

### B. Performance Faster R-CNN with ResNeXt Backbone

The ResNeXt-50 backbone offered a moderate improvement over ResNet-based architectures, achieving AP 87.4% at IoU 0.50:0.95, with slightly lower AP values than RetinaNet but outperforming ResNet-50 and ResNet-101. The model maintained an AR of 99.1%, indicating that it effectively captures diverse object instances, leading to a high detection recall. The grouped convolutions in ResNeXt likely contributed to enhanced feature aggregation and spatial sensitivity, allowing the model to detect a broader range of object scales with better contextual understanding. While ResNeXt's performance suggests an improvement in multi-scale feature representation, the relatively small AP gain over ResNet-50 indicates that for this specific detection task, its additional computational complexity does not necessarily translate into a proportionate improvement in detection accuracy.

### C. Influence of RetinaNet as a Backbone for Faster R-CNN

The integration of RetinaNet as a backbone for Faster R- CNN led to substantial improvements in detection performance, achieving an AP of 91.1% at IoU 0.50:0.95 and reaching 99.9% AP at both IoU 0.50 and 0.75. The model consistently maintained a high AR of 93.8%, demonstrating exceptional reliability in detecting positive instances across varying IoU thresholds. The superior performance can be attributed to RetinaNet's balanced handling of foreground and background samples, as its Focal Loss formulation effectively mitigates the imbalance between easily detected and hard-to-detect instances.

The marked increase in AP and AR values indicates that incorporating RetinaNet as a feature extractor enhances feature refinement and region proposal quality, leading to higher detection confidence and better localization accuracy. This underscores RetinaNet's superior feature representation capabilities, particularly in challenging detection tasks involving subtle object variations or occlusions.

### D. Comparative Analysis (Two-stage Architecture)

A comparative overview of the evaluated Faster R-CNN models is provided in Table III, summarizing their AP and AR scores at varying IoU thresholds:

TABLE III. Average Precision (AP) over Different Threshold

| Baseline FRCNN at different Threshold (IoU) | | | | |
|---|---|---|---|---|
| **Models** | **AP** | **AR** | **AP @ 50** | **AP @ 50 -95** |
| F-RCNN + ResNet_50_FPN | 0.858 | 0.996 | 0.996 | 0.858 |
| F-RCNN + ResNet_101_FPN | 0.855 | 0.889 | 0.889 | 0.855 |
| F-RCNN + ResNeXt-50 | 0.874 | 0.991 | 0.991 | 0.874 |
| F-RCNN + RetinaNet | **0.911** | **0.938** | **0.999** | **0.911** |

From the results, Faster R-CNN with RetinaNet emerges as the most effective architecture, offering the highest AP (91.1%) and AR (93.8%) across varying IoU thresholds. This suggests that RetinaNet's enhanced feature refinement and balanced detection capability make it well-suited for the accurate identification of *Ascaris lumbricoides* and *Trichuris trichiura*.

In contrast, ResNet-50 and ResNet-101 demonstrated similar performance, with ResNeXt offering a slight improvement over ResNet-based variants but falling short of RetinaNet's superior AP and AR scores. While ResNeXt enhances feature learning through grouped convolutions, its computational trade-offs may not justify its minor accuracy gains.

### E. Performance of Single-Stage YOLOv8 Architectures

In contrast to the two-stage Faster R-CNN models, single-stage architectures such as YOLOv8 offer a streamlined detection pipeline, eliminating the region proposal step and directly predicting object locations and classifications in a single forward pass. This approach is particularly advantageous for real-time applications where inference speed is critical, such as in automated parasitic detection in medical diagnostics.

The performance of YOLOv8 models was assessed across five different variants, ranging from the smallest YOLOv8n (nano) to the largest YOLOv8x (extra-large), with results presented in Table IV. Among the YOLOv8 variants, YOLOv8n (nano) achieved the highest overall precision, with an AP@50-95 of 93.8%, marginally surpassing YOLOv8x (extra-large) and YOLOv8m (medium), which also scored 93.8%. The YOLOv8l (large) and YOLOv8s (small) models exhibited slightly lower mAP@50-95 (93.6%), indicating that model scaling has

minimal impact on detection accuracy at standard IoU thresholds. Notably, YOLOv8n (nano) achieved the highest recall (mAR = 99.5%), outperforming its larger counterparts. This suggests that even with a reduced parameter count, YOLOv8n maintains strong object detection capabilities, making it an efficient choice for resource-constrained environments. Table IV summarized the results.

TABLE IV. ACCURACY-PERFORMANCE TRADE-OFFS ACROSS YOLOV8 VARIANTS

| Baseline YOLOv8 at different Threshold (IoU) | | | | |
|---|---|---|---|---|
| **Models** | **AP** | **AR** | **AP *@50*** | **mAP @ 50 - 95** |
| YOLOv8x | 0.964 | 0.990 | 0.993 | 0.949 |
| YOLOv8l | 0.976 | 0.982 | 0.993 | 0.936 |
| YOLOv8m | 0.993 | 0.986 | 0.995 | 0.938 |
| YOLOv8s | 0.982 | 0.990 | 0.991 | 0.936 |
| **YOLOv8n** | **0.994** | **0.995** | **0.994** | **0.938** |

Despite being the most computationally intensive model, YOLOv8x did not yield a significant accuracy advantage, achieving a mAP@50-95 of 94.9%, only slightly higher than its smaller counterparts. In contrast, YOLOv8n (nano) emerged as a highly competitive alternative, offering comparable accuracy while delivering superior inference efficiency. This makes YOLOv8n particularly well-suited for embedded medical imaging systems and real-time diagnostic applications, where computational efficiency is paramount.

### *F. Performance Analysis of Optimized YOLOv8n Model*

To further enhance the detection accuracy and efficiency of YOLOv8n, Bayesian Optimization was employed to determine the optimal hyperparameter configuration. This optimization approach efficiently explores the hyperparameter space, balancing the trade-offs between accuracy and computational cost. The key hyperparameters tuned and their respective search ranges are presented in Table II.

The optimized YOLOv8n model achieved an AP of 0.996 and an AR of 0.997, demonstrating near-perfect object detection capability. The exceptionally high recall (0.997) ensures that nearly all instances of *Ascaris lumbricoides* and *Trichuris trichiura* are accurately identified, significantly reducing false negatives and enhancing detection reliability. Compared to the baseline YOLOv8n (AP@50-95 = 0.938), the optimized model achieved an improved AP@50-95 of 0.947, reflecting greater accuracy across varying IoU thresholds. Additionally, AP@50 remained consistently high at 0.995, confirming that the model maintains robust detection performance even under more lenient overlap conditions.

The Bayesian-Optimized training configuration enhanced accuracy without imposing significant computational overhead, making it an ideal choice for real-time diagnostic applications. The fine-tuned learning rate, momentum, and weight decay likely contributed to improved convergence and reduced overfitting, ensuring greater generalizability across diverse detection scenarios. Fig. 4 depicts the training and validation metrics of the optimized model.

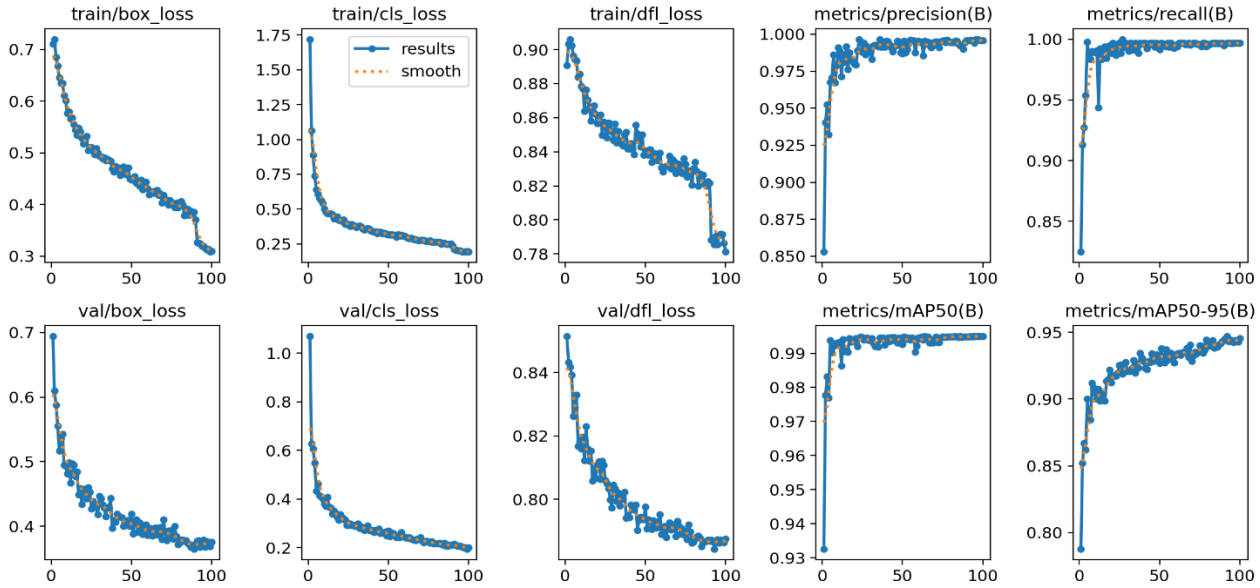


Fig. 4. Training and Validation metrics for optimized YOLOv8n model.

The qualitative detection results in Fig. 5 showcase the model's ability to accurately localize and classify parasite eggs in microscopy images, with predicted bounding boxes and confidence scores reflecting high detection reliability. The Precision-Recall Curve in Fig. 6 further validates the model's robustness, achieving a mean average precision (mAP@0.5) of 0.995 for both *Ascaris lumbricoides* and *Trichuris trichiura*, highlighting its near-perfect classification capability. The F1-Confidence Curve in Fig. 7, demonstrates the model's optimal F1 score of 1.00 at a confidence threshold of 0.740, indicating a well-calibrated balance between precision and recall. These findings underscore the model's efficacy in automated parasite detection, with significant potential for deployment in diagnostic and epidemiological applications.

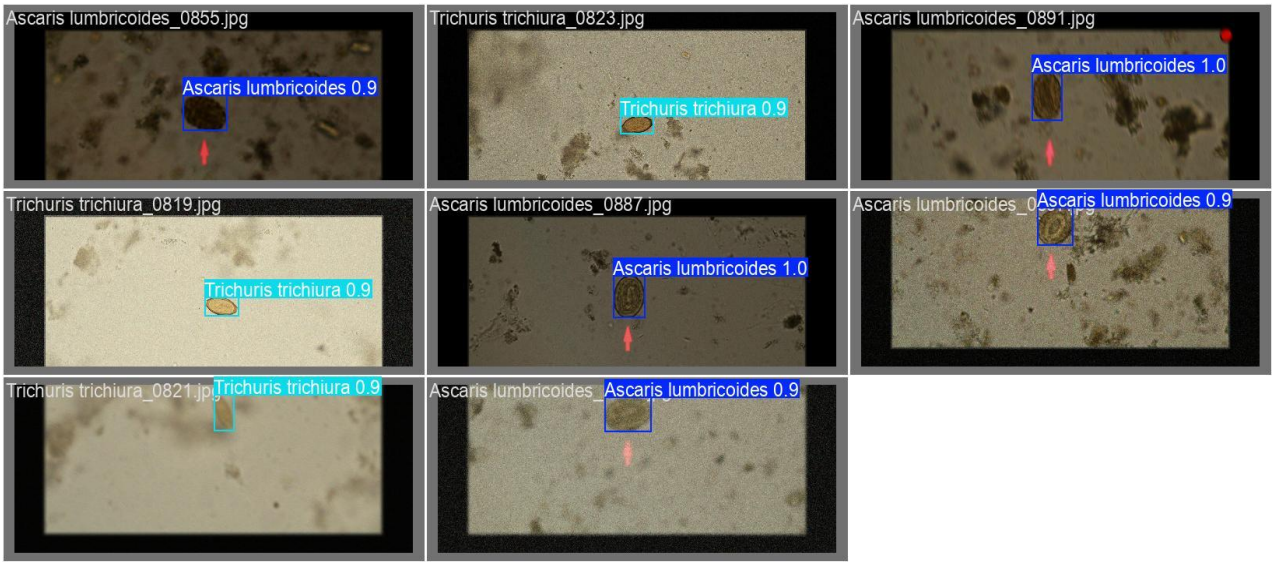


Fig. 5. Detection results of parasite eggs using optimized YOLOv8n: predicted bounding boxes with confidence scores.

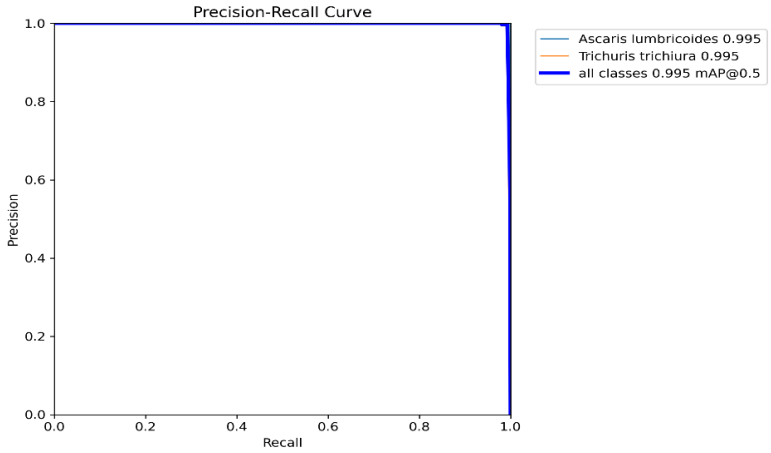


Fig. 6. Precision-Recall Curve for parasite detection: achieving 0.995 mAP@0.5 for all classes.

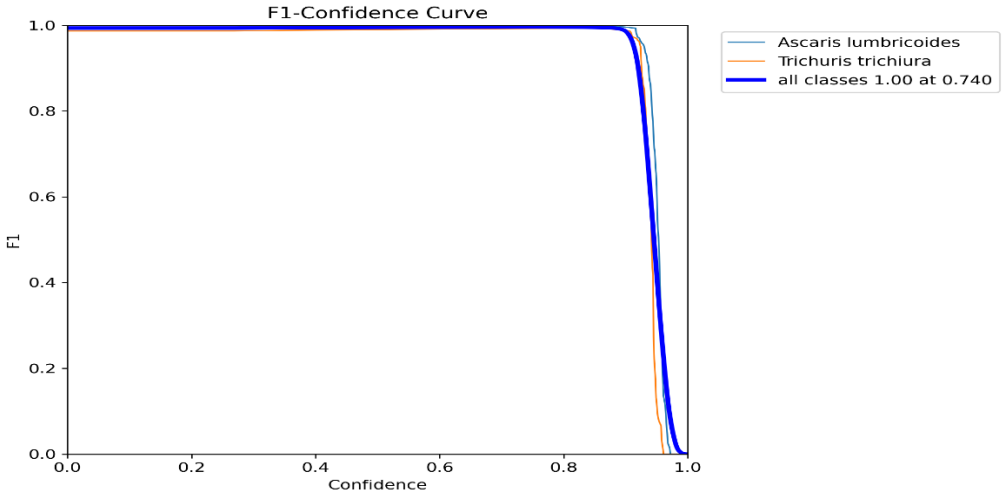


Fig. 7. F1-Confidence Curve for parasite detection: Optimal F1 score of 1.00 at 0.740 confidence threshold.

The optimized YOLOv8n achieved exceptional precision and recall, with results summarized in Table V.

TABLE V. AVERAGE PRECISION (AP) OVER DIFFERENT THRESHOLD

| Baselines with Optimized YOLOv8n at different Threshold (IoU) | | | | |
|---|---|---|---|---|
| **Models** | **AP** | **AR** | **AP *@50*** | **AP @ 50 - 95** |
| F-RCNN + RetinaNet | 0.911 | 0.999 | 0.999 | 0.911 |
| Baseline YOLOv8n | 0.994 | 0.995 | 0.994 | 0.938 |
| **Optimized YOLOv8n** | **0.996** | **0.997** | **0.995** | **0.947** |

The Bayesian-Optimized YOLOv8n demonstrates superior accuracy and efficiency, making it a powerful and practical model for real-time medical diagnostics. Compared to FRCNN with RetinaNet backbone and YOLO counterpart, including the larger YOLOv8 models, it delivers state-of-the-art precision (AP = 0.996) and recall (AR = 0.997) while maintaining its lightweight structure. This highlights the critical role of hyperparameter tuning in enhancing deep learning models for high-stakes applications such as parasitic infection detection. The following graph in Fig. 8 visualizes the trends of mean average precision for the different higher-performing models.

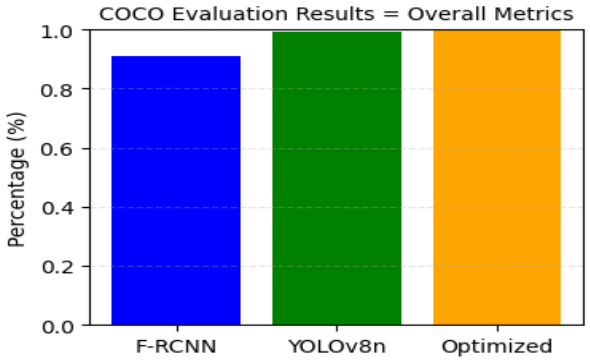


Fig. 8. Performance comparison of detection models (Faster R-CNN with RetinaNet, YOLOv8n and Optimized YOLOv8n) highlighting differences in average precision for intestinal parasite detection.

## V. CONCLUSION

This study underscores the significant potential of advanced object detection models in automating intestinal parasite detection. The evaluation of various detection models highlights the optimized YOLOv8n as the best-performing model, achieving the highest AP (0.996), AR (0.997), and AP@50-95 (0.947). Compared to the baseline YOLOv8n, the optimized version demonstrates superior precision and recall, ensuring more accurate and reliable detection across varying IoU thresholds. Furthermore, it outperforms the Faster R-CNN with RetinaNet, which, despite maintaining high recall (0.999), lags in overall precision (AP@50-95 = 0.911).

The Bayesian-Optimized YOLOv8n strikes an optimal balance between detection accuracy and computational efficiency, making it the ideal choice for real-time, high-precision medical diagnostics. Its lightweight architecture, coupled with enhanced performance, positions it as the most viable model for scalable and resource-efficient deployment in automated parasitic detection systems.

Future research can explore transformer-based enhancements like Swin Transformer to improve feature representation and localization. Self-supervised learning and domain adaptation could further refine performance in real-world clinical settings. Additionally, optimizing the model for edge AI and mobile deployment will enhance scalability for global healthcare applications.

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# A Comparative Study of Deep Learning and Modern Machine Learning Methods for Predicting Australia's Precipitation

Hira Farman[1], Qurat-ul-ain Mastoi[2], Qaiser Abbas[3],
Saad Ahmad[4], Abdulaziz Alshahrani[5], Salman Jan[6], Toqeer Ali Syed[7]
Department of Computer Science, Iqra University, Pakistan[1]
Department of Computer Science, Iqra University,
Karachi Institute of Economics and Technology, Karachi, 74600, Pakistan[1]
School of Computing and Creative Technologies University of the West of England Bristol, United Kingdom[2]
Faculty of Computer and Information Systems, Islamic University of Madinah, Madinah, 42351, Saudi Arabia[3]
Faculty of Computer Science, IQRA University Karachi, Pakistan[4]
Islamic University of Madinah, CO 42351 Madinah, Saudi Arabia[5, 7]
Faculty of Computer Studies, Arab Open University, 512, A'ali Kingdom of Bahrain[6]

***Abstract*—Floods are chaotic weather patterns that cause irreversible and devastating harm to people's lives, crops, and the socioeconomic system. It causes extensive property damage, animal mortality, and even human fatalities. To mitigate the risk of flooding, it is imperative to create an early warning system that can accurately forecast the amount of rain that will fall tomorrow. Rainfall forecasting is essential to the lives of people and is absolutely important everywhere in the world. The rainfall prediction model reduces risk and helps to prevent further human deaths. Statistics cannot reliably forecast rainfall since the atmosphere is dynamic. Due to the preceding factors, this study uses machine learning and deep learning techniques to estimate precipitation. The purpose of this study is to develop and evaluate a prediction model for forecasting rainfall of 5 cities of Australia (Darwin, Sydney, Perth airport, Melbourne, Brisbane). The Dataset was gathered from the national meteorological organization of Australia is the Australian Government Bureau of Meteorology, also known as the BOM. To monitor and forecast meteorological conditions, climatic trends, and natural calamities like cyclones, storms, floods, the Bureau of Meteorology is essential. The dataset includes 14, 5460 size, 23 features detailed city-specific monthly averages for Australia from 2008 to 2017(10 years). An effective rainfall forecasting was produced by integration of a number of Machine Learning and Deep Learning techniques, including Random Forest model (RF), Decision Tree (DT) and Gradient Boosting classifier (GBC), Artificial Neural Network (ANN), and Recurrent Neural Network (RNN). The models were trained to forecast rainfall, reducing the potential impact of floods. Results indicate that combining neural networks and Random Forests provides the most accurate predictions.**

***Keywords*—Machine learning; rainfall prediction; neural network; Random Forest; deep learning***

## I. Introduction

Natural disasters including floods, hurricanes, and earthquakes are becoming more frequent and intense due to environmental changes such as deforestation, urbanization, and climate change. Floods pose serious threats to lives, agriculture, and economies, usually it results from heavy rainfall and poor drainage system in the some of the regions. Given the growing impact of extreme weather, this study compares three LSTM-based neural network architectures to identify the most suitable model for forecasting hourly rainfall volumes. The leading purpose of such study is to use deep learning algorithms in developing flood prediction models based on meteorological data [1]–[3]. Publics and governments may be enabled to both prevent the flood occurrence with immediate and long term actions and prepare for evacuation and rescue operations with the help of the early warning in advance.The studies were conducted using data from crowdsourcing, geospatial, hydrological, and meteorological sources. In this study [4]–[6], successfully machine learning is used to build a rain forecast model. This work [7] focuses on the machine learning (ML) methods of prediction for six selected stations per semi-annual cycle in Bangladesh in order to create a new achieving format of the monthly dry days (MDD). Through the use of machine learning approaches, the study analyzes the unanticipated effects of flood protection in Bangladesh [8].The main contribution of this research [9] is to determine the state-of-the-art machine learning methods for flood prediction together with the significant parameters that were fed into the model. This will make it possible for flood management and/or researchers to compare the prediction findings to one another when assessing machine learning techniques for early flood forecasting. The study investigated the possibility of developing a probabilistic forecasting model through the employment of various machine learning techniques, including the k nearest neighbors (also called KNN)method, the fuzzy inferential model (FIM), and the support vector regression methodology (SVR). Modeling of flood conditions is a difficult task that requires an in-depth analysis of the situations that affect flooding. This study proposes an Internet of Things based flood state prediction (IOT-FSP) model to assist river flooding conditions forecast [10]–[18].

This study explores the use of machine learning (ML) and deep learning (DL) techniques to improve rainfall forecast accuracy. Grey Relation Analysis (GRA) is used to identify influential factors, while Support Vector Machines (SVM) and

Artificial Neural Networks (ANN) are applied for prediction. Specifically, a model combining Feed Forward Neural Networks, the Levenberg-Marquardt algorithm, and backpropagation is used to forecast monthly and bi-monthly rainfall in Northern India. Performance is evaluated using MSE, MRE, and regression analysis. The research not only aims to enhance prediction but also supports disaster preparedness and response planning.

### A. Purpose of the Study / Research Questions

The following are the research primary goals:

- Feature cleaning and visual representation for datasets features
- Univariate and multivariate analysis of datasets with regard to several features.
- Several models of machine learning have been experimented and have shown their accuracy in forecasting Rainfall.
- Validating deep learning's efficacy in precipitation prediction.
- Comparative analysis for different algorithms for accuracy and error for Rainfall prediction.
- In order to classify the objects with extreme speed and accuracy, the architecture of the LSTM-Deep learning network was developed.
- An extended experiment was conducted to provide a detailed examination of the proposed model.

Rainfall prediction in Australia is challenging due to regional differences, monsoon dynamics, and climate change. This study investigates five ML and DL models to improve forecasting accuracy by identifying key atmospheric variables and evaluating seasonal rainfall severity over the past decade. The study aims to (1) support early warning systems with relevant statistics, (2) provide metrics for policymaking related to rainfall management, soil degradation, and drought, and (3) enhance climate models by deepening the understanding of factors influencing weather patterns.

### B. Justification for Model Selection

In this study, we selected advanced machine learning (ML) and deep learning (DL) models such as LSTM, CNN, and SVR due to their proven ability to capture nonlinear patterns in time-series data. LSTM networks, in particular, are well-suited for sequential data such as rainfall records because they can retain long-term dependencies, which are essential for understanding delayed rainfall effects due to climate shifts. CNNs, though originally developed for spatial features, have recently shown promise in extracting local patterns in time-series signals, making them a good fit for rainfall fluctuations. Meanwhile, SVR provides a robust baseline with good generalization ability, especially in high-dimensional meteorological datasets.

Traditional statistical models, such as ARIMA or linear regression, often assume linearity and stationarity, which are major limitations when applied to rainfall data that exhibit strong temporal variability and noise. These models also struggle with multi-feature dependencies and are less adaptive to changing climate patterns. Furthermore, simpler ML models like decision trees may lack the depth required to model complex seasonal transitions or capture hidden trends across time steps, leading to reduced prediction accuracy.

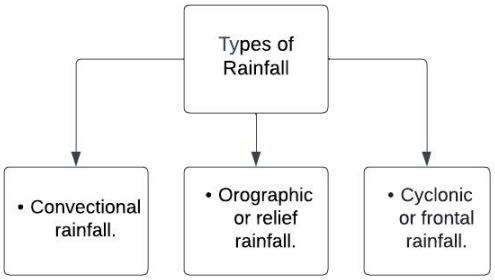


Fig. 1. Types of rainfall.

The other part of the research is organized as follows: On the other side, the theoretical context, comparative analysis, the data set and Australia Location utilized in study, and experimental methods are all presented. Following the Machine learning and Deep learning algorithms designing, which are the main part of the early rainfall prediction of the dataset based on accuracy and other measures like F1 score, accuracy, and recall, is the Results and discussion section of work, the Last section Summary and future research is a conclusion part.

## II. Related Work

### A. Types of Rainfall

Rainfall can be classified into various types based on different criteria such as duration, intensity, spatial distribution, and the mechanisms responsible for its occurrence. Here are some common types of rainfall in Fig. 1.

*1) Convectional rainfall:* As the Earth's surface warms, air rises, resulting in convectional rainfall. As it increases, the air cools and releases moisture as rain. In regions with high temperatures and high humidity, convectional rainfall is frequent, frequently occurring in tropical climates in the late afternoon or evening [19], [20].

*2) Orographic rainfall:* Orographic rainfall is the result of moist air being lifted as it is pushed over high ground, such as mountains or hills. On the mountain's windward side, moisture and precipitation result from the rising, cooling air. Due to descending dry air, the leeward side gets a rain shadow effect, which reduces rainfall [21].

*3) Cyclonic rainfall:* Rainfall associated with cyclones or low-pressure systems is referred to as cyclonic rainfall. It is characterized by persistent, widespread rain that is frequently accompanied by high winds. Forecasting weather, preparing for disasters, and managing water resources all depend on an understanding of cyclonic rainfall patterns [20].

### B. Effects of Rainfall

The understanding of rainfall effects is of great importance for several businesses, p.e. agriculture, water resources man-

agement, disaster preparedness, and climate research. For sustainable growth and risk reduction related to extreme weather events, monitoring rainfall patterns and managing its effects are essential. Here are some notable effects of rainfall, Water Supply [22], Agriculture, Moisture in the Soil and The process of erosion, Flood [4], [9], [10], [23]–[26], Hydroelectric Power Generation, Weather and Climate Patterns [2], [27].

### C. Motivation and Impact of Flood Events

Existing flood prediction models rely on complex statistical computations that are either very costly financially and computationally or aren't applicable to applications in the future. To circumvent these issues, approaches that mix time-series data with machine learning algorithms are being researched. For various downstream applications, it is necessary to compare the efficiency of deep learning architectures and conventional machine learning methods.

Here the rainfall is estimated by using a simplified model [28]. It is Southern India, Kerala that faced the flood of the century. Often, it also means a huge loss of peoples' lives and properties. This consequently prompted us to investigate the variations in the rainfall pattern of Kerala. In Bangladesh, floods kill people, destroy household properties, crops and means of livelihood of the masses constantly. Flooding is caused by lakes, rivers and other water bodies discharging water and incorporating adjacent land into the flooded region. Every year, flooding becomes the worst enemy for more than 4. In India have the 3. 84 crores people. 84 million in the case of Bangladesh and the rest in 3. 29 million in China has realized that [1].The recent event which took place in Kerala in August 2018 is one of the most remarkable incidents followed by massive floods in India , which is currently considered as one of the most affected nations with respect to catastrophic floods across the globe.

### D. Machine Learning Applications in Flood Forecasting

Much has been said in past times on Flood probability, which can be done through IoT and ML based on rainfall, humidity, water temperature, water velocity, and other variables. There are some limitations in the research since we have not tried to establish the probability range for flood based on the levels of temperature and rain intensity. Scientific communities all over the globe are interested in developing flood forecasting methods. Thus, there is a demand for flood forecasting that must be high-quality and reliable so that those living near the flooded areas can have the warning signs that they need to evacuate. Thus, a 5-hours flood simulation of rainfall area for Kuala Lumpur city in this study was provided using neural network's Autoregressive Structure with Extended Input (NNARX) and its Enhanced Modeling. This work [29] combines ML technology with established ones to generate models that have more prediction yield than other existing models. The main value of this study is in the fact that it highlights the current trend of using ML models for flood prediction as well as giving suggestions of the best kinds of models to use. This analysis is mainly focused on the empirical research of ML approaches in the area where the models have been evaluated for robustness, accuracy, utility, and speed.

### E. Model Evaluation, Datasets, and Techniques

To make the research more detailed and accurate, the area of interest is divided into grids delimited by latitude and longitude, with precipitation and flow readings merged into vector organizations based on coordinates. The input property consists of a two-dimensional timeline containing spatial information instead of a one-dimensional timeline. The first step which is the focus to extracting spatial and temporal components of hydrological information is comprised of.In particular the author introduces the convolutional LSTM (Con LSTM), which combines the Convolutional Neural Network (CNN) and Long Short Term Memory Network (LSMN) to boost performance. The aim of this work is to design a flood prediction system which can be used as an advantageous instrument for urban administration and resilience management through an integration of machine learning algorithms and GIS techniques [30]. This method will lead to development of long-term strategic policies for the growth of smart cities that will be workable and suitable flood indicators at the level of the municipality. At the Random Forest algorithm with the accuracy 0% . 0.96, and a Pearson's (or linear) coefficient of 0. 77 was an excellent choice as the input layer or the hidden layer of machine learning as it can identify errors. This requires summarizing different past research studies that examine the ML techniques for flood forecasting and the characteristics which are used for the forecast. Goal of the research is to find flood forecasting approaches which mainly involve ML techniques and to determine flood prediction parameters that have been used as input parameters to the models for forecasted flooding in order to achieve that. The most valuable aspect of this work is the list of critical variables and recent ML methods employed for flood prediction. They may be able to then both carry out short- and long-term preventive measures, be proactive and rescue people and provide relief for flood victims, with the help of an early warning of a flood disaster [31]. For example, one of the main factors in most flood management is the geographic location of the affected areas and their respective severity.

### F. Recent Developments and Future Directions

Floods cannot yet be reliably predicted in advance with the help of any approach. Data that was prepared and manually entered was typically used by earlier technologies. It was not possible to make early and real-time estimates due to the lengthy processes. In order to forecast flood events in particular regions and time periods, this research proposes a novel approach to flood forecasting that integrates meteorological, hydrological, spatial data, and big data from crowdsourcing sources. System that takes into account both historical data and climatic conditions produced the most precise estimation by the setup using an MLP ANN for the Correct proportions, Kappa, MAE, and RMSE 97%. 0. 89, 0. 93, 0., and 0. 10, respectively. In this [32] research cutting-edge operating methods have been investigated. The current move towards data-driven strategies for flood prediction is something that the writers see and discuss. Forecasting tasks are becoming more and more relevant for machine learning-based models that were trained using historical data for climatic parameters.

The main objective of this work is to demonstrate recent advances in machine learning-based flood forecasting. To

develop their conclusions, the authors looked at various widely used flood prediction techniques that different specialists might use. In study [23] create a probabilistic forecasting model, this study used a variety of machine learning techniques, such as k nearest neighbors (KNN), fuzzy inference models (FIM), and support vector regression (SVR).In order to lessen the harm caused by flooding, an examination of the utilization of information gleaned from urban rivers to forecast floods is done in this work [24]. The Artificial Neural Networks were examined to determine their level of accuracy in the forecasting models after the immersion theorem had proven the interdependence of the data. Whenever there have been significant flooding-related difficulties, WSNs have been installed. The study's methodology [33] may help improve the early warning systems that are in place now and generate risk-based development plans. Uncertainties in machine learning-based geospatial algorithms for flood prediction are resolved using a unique method. This paper proposes a method for decreasing regional disparity along with four distinct and hybridized ML based flood susceptibility models (the FSMs). In order to forecast and identify the flooding sites or flood sensitive zones in the Teesta River a basin, this study [4] applied cutting-edge revolutionary ensemble machine learning algorithms. The purpose of the work being done is to construct a rain prediction model using the successful machine learning Random Forest [5]. The goal of this study [6] is to reduce the significant hazards associated with this natural disaster while also making recommendations for policy. To generate an accurate forecast, this study will make use of a Decision Tree classification technique, K Nearest neighbor(KNN), a Support Vector Classifier(SVC), and Binary Logistic Regression(BLR).The findings will be compared to identify the model with the highest level of accuracy. In this study [34], the author used the k-nearest neighbor's algorithm to predict a flood using various correlation coefficients for feature selection. It is well-known that estimating flood risk and making informed decisions [35] depend greatly on quantifying and reducing the uncertainty related to the hydrologic forecast. This article provides a thorough analysis of Bayesian forecasting techniques used in flood forecasting. In this research, 180 independent models based on five diverse machine learning algorithms that include the exponential back propagation neural network('EBPNN'), multilayer perceptron(MLP), support vector regression(SVR), Decision Tree regression(DT Regression) and extreme gradient boosting(XG-Boost), were developed. The "Someshwari Kangsa" sub-watershed of the Bangladeshi arterial north-central hydrological zone containing an area of 5772 square kilometers was used by models. Indeed, it is a difficult task to make a forecast on the upcoming rain by means of classic machine learning algorithms. Besides that, various attempts have been also made by employing different computer techniques to forecast rainfall. To build the long term memory rainfall module of Bangladesh, this article applies the technique of the feedforward architecture driven long short term memory (LSTM) networks that gets rid of the chaos related problems of the different methods. In Bangladesh, this work proposes a novel approach to forecasting monthly dry days (MDD) at six specified recourse stations and then examining the outcomes of the models. The MDD and MWD datasets in terms of monthly dry and wet days, respectively, were done using different rainfall thresholds. This research, although suggested by simply posing the question of 'what will be the consequences of flood mitigation methods in Bangladesh in the long-run' [8] is highly recommended. Data from the historical events (represented by the emigrations and mortality rates) and economic surveys accumulated from 1983 to 2014. The primary objective in this study [36] is the significance of being responsible for and taking care of disasters which humans bring on themselves. Technology that is now in use, software Artificial (AI) can be used for these tasks. Review work and comparison of different approaches and algorithms used by researchers to estimate rainfall are presented in tabular form [37]. Making methods and procedures used in rainfall forecasting understandable to non-experts is the aim of this endeavor. One notable illustration of how India is currently among the nations in the world that have experienced the most severe flooding is the most recent disaster that occurred in Kerala in August 2018. Much work has been done in the past to use Internet of Things, or IoT, and ML (machine learning) approaches to assess the likelihood of flooding based on rainfall, humidity, water temperature, water velocity, and other characteristics. The prime output of this study is to review the ML models used for flood forecasting as current models and give advice on how to choose the best models. India [27] is in more danger for floods that cause grave losses now; last August extreme floods happened in Kerala and it illustrates the disasters from this catastrophe. The problem is that the flood frequency model is based solely on historical data from the past – number of rainfall events and their water temperature. The neural network has been employed that is Deep Learning to calculate probabilities of flooding considering temperature and rainfall intensity. Consequently, with the flooding having taken over as one of the most well-known subjects of research in hydrology, flood prediction has become one of the principal areas of focus of hydrologists. The issue has been addressed by a lot of researchers with different methods, starting from image processing to physical models, still, are not at the level that can accommodate all applications due to imprecision and insufficient time steps. It studies deep learning methods in gauge height prediction, and also the error in gauge height prediction is assessed. For constructing and verifying the model, the measured height data from Valley Park, Missouri's Meramec River was implemented. According to an analysis based on previous research articles, this study looks at whether the present machine learning (ML) algorithms for flood forecasting are effective given the variables that are used to predict floods. The manifold model is represented here [38] as a machine learning substitute to hydraulic modeling of flood waters. All model achieves performance standards that are tuned to operational use, provided historical data has been used as a benchmark. The article proposes a system that predicts possible floods in a river basin using machine learning and the Internet of Things (IoT) for the research [25].The model connects the Wireless Sensor Network, or WSN, to a personalized mesh network via a ZigBee connection, and it then uses a GPRS module to transmit data over the internet.For predicting the occurrence floods occurrences in the Pattani River, this work [26] examines applying possible machine learning algorithms using open data. This study [23] employed a combination of machine learning tools, such as support vector regression (SVR), fuzzy inference model (FIM), and the k-nearest neighbors (k-NN) method in order to develop a probabilistic forecasting model. This study takes a probabilistic forecasting model with the help of a number of machine learning approaches, including SVR model (a support vector regres-

sion model), fuzzy inferential models (FIM), and the KNN technique (the K nearest neighbors technique). In total, three multi criteria decision making evaluation approaches, namely VIKOR, SAW, and TOPSIS, along with two machine learning methods, NB and NBT, were utilized to assess their ability to simulate flood vulnerability in the Ningdu Catchment[Complex Flow of Words] which is one of China's most flood-prone regions [39]. Two techniques, Extensive gradient boosting This experiment is based on the Deep Belief Network (DBN) for forecasting the Daya and Bhargavi river banks, which flow towards the Indian state of Odisha. A comparison study that is based on other machine learning methods helps to demonstrate the beneficial impacts of dams in detail. This study [40] focuses on the application of ant colony optimization (ACO), Genetic algorithms (GA), artificial neural networks (ANN), and Particle swarm optimization (PSO) approaches to flood hydrograph prediction. In the current study [41], the relative accuracy of the RB FNN, SVM, and Firefly Algorithm (FA) models compared to the regular ANN, RB FNN, and SVM algorithms for river flood discharge forecasting in the Barak River was examined. Urban flooding is becoming increasingly common [42], which is detrimental to both the economy and quality of life for people. However, the existing flood prediction algorithms have grown too primitive or insufficient to accurately capture the details of flood evolution.This study uses deep neural networks to quicken the computation of a physics-based 2D urban flood forecasting approach that uses the Shallow Water Equation (SWE). Using data modeled by the use of a partial differential equation (PDE) solver, convolution neural networks (CNN) and generative adversarial networks with conditions (CGANs) are utilized to identify flood dynamics. The four ML-based FSMs Fandom Forest (RF), K nearest neighbor (KNN), multilayer perceptron (MLP), and hybridized genetic algorithm–Gaussian radial basis function–support vector regression (GA;RBF;SVR) shown in this article [43]—present a framework for reducing spatial disagreement. The outcomes of those four models were combined to generate an enhanced model as well. The approach presented in this study may be useful in developing risk based development plans and enhancing current early warning systems. This paper [44] utilized a deep learning-based model to predict the water level flood phenomenon of a river in Taiwan. The experimental results showed that the Conv GRU neural network model performed better than other current methods. The trial's outcomes showed that the suggested method could correctly identify the wrong water levels. The purpose of this study project [45] is to use artificially intelligent neural network (ANN) modeling techniques and Lavenberg Marquardt (MLR) multiple linear regression to determine long-term seasonal rainfall patterns in Western Australia.This study [46] demonstrates how RBFs, which are both linear and nonlinear kernel functions, can produce superior results in the same catchment under various conditions. Lighter rainfalls would provide quite different responses from bigger ones, which is a highly helpful technique to disclose the behavior of an SVM model. The study also demonstrates an unexpected result in the SVM reaction to various rainstorm inputs. The process of predicting flood status is difficult [10] and necessitates thorough investigation of the causes of flooding. In order to make it easier to foresee the situation with rivers flooding, this research suggests an Internet of Things-based flood status prediction (IOT-FSP) model. The IoT-FSP model utilizes the Internet of Things architecture to facilitate the collection of flood data as well as algorithms for machine learning (ML) for flood prediction: Decision Tree (DT),Random Forest (RF).This research predicted the flood prone areas in Nigeria using historical flood records [11] from 1985 to 2020 and a number of variables that were confounding. Both logistic regression (LR) and ANN (artificial neural network) algorithms were trained and evaluated to determine the relationship between flood occurrence and the fifteen (15) explanatory factors, which include topographic, meteorological land utilization, and proximity information. This resulted in the creation of a flood susceptibility map. This study [12] explores how several machine learning algorithms can be used to create the most accurate flood determining model. This work proposed three novel machine learning models: the multivariate adaptable regressed splines (MARS), the boosted regression model (the BTR), and the generalized additive model (the GAM) [13]. The province of Ardabil, one of the lands near the Caspian Sea coast, which is regularly affected by flooding, was chosen for applying the methodology that the study referred to. The objective of this study is to figure out how the rainfall Figure time-series data from eight stations along the Kelantan River and the corresponding discharge values influence water level accuracy at Kuala Krai downstream [14]. Another approach of pre-processing involves using of Data Unpredictability and Mutual Information (MI) to recover necessary information to be used as attributes for the forecast model. In this study, the author developed an early flood warning model by using the input and the output layers of multilayer perceptron with stream specification to forecast incoming water level. This research aims to discuss the incorporation of machine learning to trace rain patterns [16]. To do this, a collection of data representing the estimates of rainfall seen in Australia's major cities over the past ten years was subjected to the four main machine learning techniques: K-nearest neighbors (KNN), Decision Tree (DT), Random Forest (RF), and Neural Networks (NN). This study [17] represents the accuracy of rainfall forecasting models engaged by modern machine learning algorithms in forecasting rainfall volume of hours using weather series time information from UK cities. The results clearly indicate that neural nets perform best. This work [18] examines the flood hazard analysis in the Turkish province of Bitlis using the analytical hierarchy approach, a multi-parameter modeling tool.

The main goal of this [47] is to estimate rainfall by utilizing machine learning and deep learning techniques to identify trends in historical meteorological data. The results of this study showed that long short-term memory (LSTM), polynomial regression, and Random Forest regression performed at the greatest levels. The R2 values for polynomial regression and Random Forest are 0.76 and 0.09, respectively, whereas LSTM has a loss value of 0.09. The three different algorithms seem data mining approaches that are often employed in weather prediction; they are successful and have a solid theoretical basis in the computing model for hourly forecasting of rainfall [48]. The author of this study [49] employed three algorithms to forecast rain, using ROC curves, Brier scores, and confusion matrices as validation parameters. The input data is a ten-year panoramic set comprising 3528 datasets and 8 features from the Kemayoran Meteorological Station in Jakarta (96745).The Indian Meteorological Department in Pune contributed data from many meteorological stations in

North India, which were used in this study [50]to analyzes rainfall records spanning 141 years. Using monthly rainfall data, the Artificial Neural Network (ANN) method has been used to create forecasting models for rainfall prediction one to two months in advance. These models make use of the Levenberg-Marquardt training function and the Feed Forward Neural Network (FFNN) with Back Propagation approach. Regression analysis, Mean Square Error (MSE), and Magnitude of Relative Error (MRE) have all been used to evaluate the performance of both models. .The study [51] probably explores the methods used in the rainfall forecasting model, outlining the fundamental ideas and workings of SVR, regression, and the hybrid SVR-PSO methodology. The SVR model's incorporation of Particle Swarm Optimization offers an optimization method to enhance the prediction power. For this particular meteorological application, the comparison might shed light on the possible benefits of adopting SVR and the SVR-PSO hybrid over conventional regression models. According to studies, the ANOVA RBF Kernel offers the best forecasting accuracy with the minimum RMSE value, making it an excellent kernel to employ with the SVR-PSO approach for rainfall forecasting. This study [52] uses ensemble models, optimized artificial neural network models, and large climate indicators to predict rainfall. Accordingly, the new MLP and RBF NN models, as well as the novel hybrid GT and ensemble, were the primary innovations of this study. Not only can the ensemble models of the current work be utilized to predict rainfall, but they can also be employed to predict other meteorological data. Also examined was the uncertainty of the input data and model parameters. A hybrid gamma test was used to pick the inputs, which is a novel approach to input selection (GT).To develop a new test for selecting the optimal input situation, the GT was combined with the NMR method. The hybrid approaches [53] utilizing ACO and three different neural network architectures are presented in this study. ACO+ Feed-Forward back propagation, ACO+cascade-Forward back propagation, and ACO+ Pattern Recognition NN Classifier were the hybrid methods that were put out. The ACO Method and Neural Network are combined to create the techniques. Results of a comparison of the performance of the suggested and current models were given. It has been discovered that the suggested techniques outperform the current Feed-Forward, cascade-Forward, and Pattern Recognition NN Classifiers in terms of performance. This study [54] proposes an improved technique for creating daily short-term and monthly long-term ensemble weather forecasting models for rainfall predictions. This is achieved by combining five rainfall prediction models (Naïve Bayes, C4.5, neural network, support vector machine, and Random Forest) using three linear algebraic combinations: maximum probability, average probability, and majority vote. Using the Malaysian state of Selangor, daily weather data over a six-month period (2010–2015) yielded 1581 occurrences, which were categorized into two groups. There are two classes of rainfall: "active rainfall," which has 428 instances, and "no rainfall," which has the remaining instances. This initiative [55] aims to use feature selection and machine learning approaches to create the most accurate rainfall forecast model possible. Prior to and following feature selection, the Artificial Neural Network (ANN) attains a maximum accuracy of 90% and 91%, respectively.This research in [19] primary contribution is to identify the most recent machine learning techniques for flood prediction as well as the noteworthy parameters that were used as model input. This will allow scientists and/or flood managers to use the prediction results as a reference when evaluating ML methods for early flood prediction.

### G. Comparative Analysis

This research is intended to provide the basic framework for using machine learning and deep learning algorithms for rainstorm forecasting. To illustrate an instance, a dataset for rainfall indicators, weather information and related variables from capital cities of Australia in the last ten years is given. Table I represents the sum up of the benchmarking machine learning algorithms, strategy and input parameters that have been used in different rainfalls and floods predicting events.

### H. Discussion on Past Studies

Over time, the scientific community has paid close attention to rainfall prediction due to its complexity. Previous research on rainfall prediction has used a variety of approaches, from complex machine learning algorithms to statistical models. Here's a summary of some important findings from earlier research on rainfall prediction. In the past, researchers have used a variety of data sources, such as satellite imaging, climate models, and meteorological measurements, to forecast rainfall. Features including wind speed, humidity, temperature, the land, atmospheric pressure, and oceanic conditions are often extracted from these data sources. Rainfall data's temporal and spatial characteristics must be considered in order to fully represent its complex patterns.. Because machine learning approaches can capture nonlinear correlations and manage enormous datasets, they have become popular for rainfall prediction. Popular Deep learning model Neural networks, and supervised machine learning algorithm Decision Tree (DT), support vector machines(SVM), and Random Forests(RF) are some of the methods that easily capture non linearity from data and are utilized for rainfall prediction. Rainfall prediction is inherently uncertain due to the chaotic nature of atmospheric processes and the influence of various factors such as climate change, El Niño-Southern Oscillation (ENSO), and local topography Deep learning models LSTM and ANN are presently the main techniques for rainfall forecasting, with a focus on machine learning. Using meteorological radar data, this study [57] used LSTM networks to predict short-term rainfall in mountainous areas. The results showed promise in terms of lead time and prediction accuracy. In contrast to conventional methods, this study [58] showed how feed forward neural networks (FNNs) can be used to capture complicated rainfall patterns and improve forecast accuracy when used for rainfall prediction in arid environments. Regardless many difficulties, supervised machine learning has several potential applications in rainfall prediction hourly, seasonally, daily, monthly. To fully achieve the potential of machine learning, ongoing research, data collection, stakeholder involvement, and the integration of ML with conventional modeling techniques will be required. This research applies a combination of pre-trained convolutional neural networks and long short-term memory networks to predict rainfall. Along with the achievements and discoveries described above, there are also a lot of other innovations in terms of implementation of deep learning or DL and machine learning or ML towards Rainfall forecasting. However, the prior research had a number of limitations and

TABLE I. A COMPARISON OF WORKS OF LITERATURE THAT MAKE USE OF RAINFALL OR FORECASTS OF THE WEATHER

| Ref | Country | Region | Dataset Description | Algorithm | Accuracy | Best Accuracy | Prediction Type |
|---|---|---|---|---|---|---|---|
| [28] | UK | Bath, Bristol, Cardiff, Newport, Swindon | Past data from the UK cities Open Weather 5 dataset from Jan 2000 to Apr 2020 | Xg Boost Auto ML, LSTM-Network | Loss: 0.0014–0.0001 RMSE: 0.037 MAE: 0.009 RMSLE: 0.0072–0.0015 | Stacked-LSTM RMSE: 0.037–0.0084 MAE: 0.0071–0.001 RMSLE: 0.015–0.0037 | Rainfall Prediction |
| [2] | Bangladesh | Dhaka | Yearly flood data near 34 stations (1980-2020) | Logistic Regression (LR), SVC, KNN, DT | LR: 0.8676, SVC: 0.8088, KNN: 0.8235, DT: 0.8088 | Logistic Regression | Flood |
| [3] | Kuala Lumpur | Kelang River at Petaling Bridge | Real-time Rainfall data (19/11/2010 - 21/11/2010) | NNARX, Gradient Descent Back Propagation | Best Fit: 89.822%, Prediction Error: 0.0041 m | Loss Function RMSE: 0.0634 m, (V) 0.0040 m | Water Level Check |
| [56] | Urban | Lisbon | Data from Jan 2013 to Dec 2018 (52584 observations) | Random Forest (RF), GIS | RF: Accuracy 0.96, MCC: 0.77 | Combined Hot Spot with RF Model | Flood Prediction (Hourly Data) |
| [31] | Thailand | Surat Thani and Nakhon Si Thammarat | Excessive 5-year and 100-year return period | DT, RF, Naïve Bayes, MLP, RBF, SVM, Fuzzy Logic | MLP ANN: 97.83%, SVM: 96.67%, RF: 96.67% | MLP ANN, SVM, RF | Flood Forecasting |
| [23] | Taiwan | Yilan River basin (Liwu station) | Hourly Rainfall Data (2012-2018, 6 gauges) | KNN, Support Vector Regression (SVR), Fuzzy Inference Model | RMSE: 0.07, CE: 0.99 (1-hour) | SVR, Fuzzy Inference Model | Hourly Forecasting |
| [24] | Brazil | São Carlos, São Paulo | Rainfall in April 2014 (days:hours:min format) | Chaos Theory, MLP, E-RNN | MLP: $R^2$=0.994 | MLP (Multi-layer Perceptron) | Flood |
| [33] | Bangladesh | Southwestern Coastal Region | Yearly Flood Data (BARC) | MLP, KNN, RF, Genetic Algorithm (GA;RBF;SVR) | MLP: 0.967, KNN: 0.956, RF: 0.984 | Optimized Model: 0.987 | Flood |
| [4] | Bangladesh | Teesta River basin | 206 Non-Flood Locations selected randomly | Bagging Classifier (RF, RT, M5P, REPtree) | M5P: AUC=0.945 | Bagging Models (RF, REPtree, RT) | Flood Spot Detection |
| [5] | Bangladesh | Multiple Cities | Dataset from 2016-2019 (2391 records) | DT, KNN, LR, NB, RF | RF: 87.68% | Random Forest (RF) | Rainfall Prediction |
| [6] | Bangladesh | Gazipur, Rangpur, Barisal Districts | Rainfall Data (2011–2020) | DT, RF, SVM, NN | BLR: 0.8676 | Binary Logistic Regression (BLR) | Rainfall |
| [34] | Bangladesh | 32 Districts | 65 Years of Meteorological Data | KNN | K=2: 92.8%, K=3: 93.4%, K=4: 93.7%, K=5: 94.2%, K=6: 94.5%, K=9: 94.7% | Best Accuracy: 94.91% | Flood Prediction |
| [23] | Taiwan | Yilan River Basin (Liwu station) | Hourly River Data (2012-2018, 15 floods) | SVR, Fuzzy Inference Model, KNN | 90% CI: Acceptable Results | Probabilistic Forecasting | Real-Time Probabilistic Flood Forecasting |
| [45] | Western Australia | Marradong, Quanbun Downs, Sturt Creek | Rainfall Data (1957-2013) | MLR, ANN | Coefficients: 0.35 to 0.93 (MLR) | Superiority of Non-Linear Modeling | Seasonal Precipitation Forecast |
| [15] | France | Gardon_d'Anduze River | Hydrometric Data (2002-2018) | MLR, ANN | Nash Criterion: 0.9381 | Satisfying Outcomes | Flood Prediction |
| [55] | Australia | Nationwide | 10 Years Data (145460 rows, 23 attributes) | NB, DT, SVM, RF, Logistic Regression, ANN, PCA | ANN: Accuracy 91% | High Accuracy ANN | Rainfall Classification |

flaws. Limited availability of high-quality and spatially dense rainfall data poses challenges for model training and validation. Overfitting, especially in complex machine learning models, can lead to poor generalization performance, particularly when dealing with short and noisy time series data. Many models perform poorly in novel contexts because they over fit to datasets

ML models have the ability to accurately predict rainfall; nevertheless, there can be a lack of interaction between them and decision support systems (DSS) to facilitate real-time decision-making. -User-friendly interfaces, interoperability, and seamless integration are essential to guaranteeing the practical applicability of machine learning-based forecasting systems. Interpretability and explain ability are often lacking in machine learning models, particularly deep learning models, which makes it difficult for users to comprehend how predictions are made. This restriction impedes decision-making, adoption, and trust in operational forecasting applications.

## III. METHODOLOGY

### A. Dataset Description

A dataset gathered from the kaggle platform constituted a basis for the work discussed in the article. As indicated in Table II, the data collection covers a sample of 145,460 entries with information on 23 research variables. The values provide meteorological information that was compiled over a ten-year period from 49 distinct Australian cities. The target parameter for the machine learning and deep learning algorithms' prediction task is a Boolean variable named "Rain Tomorrow" indicating yes or no as to whether it will rain tomorrow. Similarly Table II displays the dataset's dimensionality as compared to benchmark studies. Comparison Benchmark Dataset (Rainfall Prediction Attribute) is presented in Table II .

TABLE II. COMPARISON OF INPUT PARAMETERS/ATTRIBUTES USED IN PREVIOUS PAPERS

| Ref No | Input parameters/Attribute Used in Previous Paper | Dimensionality of the datasets was downsized | Our work features |
|---|---|---|---|
| [28] | Pressure, moisture, wind speed, wind level, visibility of clouds, temperature, and time zone, Snow, rain, and snow all in three hours. | 11 features | • 'Date'<br>• 'Min Temp'<br>• 'Max Temp'<br>• 'Rainfall'<br>• 'Evaporation'<br>• 'Sunshine'<br>• 'WindGustSpeed'<br>• 'WindSpeed9am'<br>• 'WindSpeed3pm'<br>• 'Humidity 9am'<br>• 'Humidity 3pm'<br>• 'Pressure 9am'<br>• 'Cloud9am'<br>• 'Cloud3pm'<br>• 'Temp 9am'<br>• 'Temp 3pm'<br>• 'Location'<br>• 'WindGustDir'<br>• 'WindDir9am'<br>• 'WindDir3pm'<br>• 'RainToday'<br>• 'RainTomorrow'<br>• 'Pressure 3pm' |
| [2] | State, district, year, month, rainfall, max temp, min temp, flood occurrence | 8 features | |
| [56] | Measurements of humidity, temperature, exposure to the sun, rainfall, velocity of the wind, and speed of wind are included in the dataset | 6 features | |
| [33] | Aspect, Elevation, Slope, Curvature, Land Subsidence, Precipitation, Flow accumulation, SPI, TWI, Land cover, Soil texture, Soil permeability, Distance to drainage channels, Distance to rivers | 14 features | |
| [4] | Topographic factors such as elevation, slope, curvature, aspect, STI (Topographic Wetness Index), SPI (Standardized Precipitation Index), and TWI (Topographic Wetness Index), LULC (Land Use and Land Cover), rainfall, distance to the river, and soil type are the twelve factors which can be selected. | 12 parameters | |
| [5] | MaxTemp, MinTemp, Actual Evaporation, Relativehumidity9am, Relative humidity 2 pm, Sunshine, Cloudy, Solar Radiation, Rainfall | 9 features | |
| [6] | On an annual rate, from January to December: Flood, Station; April; May; June; July; August; September; October; November; and December. | 16 features | |
| [34] | Precipitation, the amount of cloud cover, the humidity level, the lowest temperature, the speed of the wind, etc. | 5 features | |
| [27] | Temperature and Rainfall | 2 features | |
| [45] | Seasonal rainfall and climate | 2 features | |
| [15] | Flooding incidents are used to train and test models: (i) 09-10 November 2018, (ii) 09-10 September 2002 | 25 events | |
| [59] | Water cut, saturation perforation, supplied petroleum radius, density of perforations, controlling area, controlled reserves, thickness of reservoirs, degree of drilling process, hole radius, flow bottom, and hole pressure, Permeability | 13 features | |

### *B. Numerical and Categorical Weather Feature Used as a Predictor*

Fig. 2, displays the missing values in each feature of the dataset in a more comprehensive manner. The yellow bars indicate missing values, while the purple bars represent available data. The columns correspond to the features in the dataset, and the figure illustrates the distribution of missing values across all variables.

Fig. 3 shows the behavior of all features, and Table III provide descriptions of the numerical characteristics together with details on their kind, availability of data, and units. Table IV define the numerical feature description with type and unit.

In this context, the eight compass points - North (N), Northeast (NE), East (E), Southeast (SE), South (S), Southwest (SW), West (W), Northwest (NW), - as well as the points in between are the wind features. Table IV has one more feature that includes two ways to display data i.e. unit, kind, category, and having data or not.

### *C. Correlated Features in the Dataset*

Breaking the date feature in month day year and the Fig. 5 showing the strong and weak correlation with the features. Tuples of Highly positively & strongly Correlated Features in overall Continent are provided in Table V.

### *D. Locations of Study Area*

In this research the effect of the data's location was looked at. The weather may vary too much in places that

TABLE III. METEOROLOGICAL NUMERICAL FEATURES DESCRIPTION

| No | Name | Features Brief Description with Units | Type | Unit | Missing Value | Available Data |
|---|---|---|---|---|---|---|
| 1 | 'Date' | The complete day date and of rainfall occurrence | string | (No unit) | 0 | 145460 |
| 2 | 'Min Temp' | The lowest temperature that a certain day might experience. | decimal | Celsius (°C) | 1485 | 143975 |
| 3 | 'Max Temp' | The maximum temperature recorded on a particular day. | decimal | Celsius (°C) | 1261 | 144199 |
| 4 | 'Rainfall' | Rainfall on a specific day. | decimal | millimeters (mm) | 3261 | 142199 |
| 5 | 'Evaporation' | Drying on a specific day. | decimal | millimeters (mm) | 62790 | 82670 |
| 6 | 'Sunshine' | On a certain day there was bright sunshine. | decimal | hours | 69835 | 75625 |
| 7 | 'Wind Gust Speed' | Strongest wind gust's speed on a given day. | decimal | kilometers per sec | 10263 | 135197 |
| 8 | 'WindSpeed9am' | Wind speed for 10 minutes before 9 am. | decimal | kilometers per sec | 1767 | 143693 |
| 9 | 'WindSpeed3pm' | Wind speed for ten minutes before three o'clock. | decimal | kilometers per hour (km/h) | 30622 | 142398 |
| 10 | 'Humidity 9am' | The percentage of the wind's humidity at 9:00 am. | decimal | percentage (%) | 2654 | 142806 |
| 11 | 'Humidity 3pm' | The percentage of the wind's humidity at 3 PM. | decimal | percentage (%) | 4507 | 140953 |
| 12 | 'Pressure 9am' | Atmospheric pressure at the time 9am it was observed | decimal | hectopascals (hPa) | 15065 | 130395 |
| 13 | 'Pressure 3pm' | Atmospheric pressure at 3 PM the observed time | decimal | hectopascals (hPa) | 15028 | 130432 |
| 14 | 'Cloud9am' | Areas of the sky that are clouded in at 9:00 am. | decimal | (No unit) | 55888 | 89572 |
| 15 | 'Cloud3pm' | Areas of the sky that are clouded in at 3 PM. | decimal | (No unit) | 59358 | 86102 |
| 16 | 'Temp 9am' | Temperature of rainfall at 9 am | decimal | Celsius (°C) | 1767 | 143693 |
| 17 | 'Temp3pm' | Temperature of rainfall at 3 PM | decimal | Celsius (°C) | 3609 | 141851 |

TABLE IV. METEOROLOGICAL WIND FEATURES DESCRIPTION

| No | Name | Description | Categories in Specific Feature | Percentage | Type | Unit | Missing Value | Available Data |
|---|---|---|---|---|---|---|---|---|
| 1 | Wind Gust Dir | The wind's direction over the 24 hours leading up to midnight (sixteen compass points) | ENE, ESE, N, NE, NNE, NNW, NW, S, SE, SSE, SSW, SW, W, WNW, WSW, NaN | NA 7%, W 7%, Other (125219) 86% | string | (No unit) | 10326 | 135134 |
| 2 | Location | Specific name of the Australian city where rainfall was recorded | Newcastle, Albury, Badgerys Creek, Cobar, Coffs Harbour, Moree, Wagga, Williamtown, Wollongong, Canberra, Tuggeranong, Mount Ginini, Ballarat, Bendigo, Sale, Melbourne Airport, Melbourne, Woomera, Albany, Witchcliffe, Pearce RAAF, Perth Airport, Perth, Salmon Gums, Walpole, Hobart, Launceston, Alice Springs, Darwin, Katherine, Uluru | Canberra 2%, Sydney 2%, Other (40676) 95% | string | (No unit) | 0 | 145460 |
| 3 | Wind Dir 9am | The direction of the wind in the first ten minutes before 9 am | WNW, ENE, NE, SSW, ESE, NW, S, W, SW, NNE, NNW, N, SE, E, SSE, WSW | SE & WW 0.07%, Others 0.06% | string | (No unit) | 10566 | 134894 |
| 4 | Wind Dir 3pm | 10 minutes before 3 o'clock the wind's direction | SSE, NNW, ENE, NNE, WENE, WSW, SSE, SW, NW, N, ESE, ENE, SSW, others | N 0.087%, Other less than 1% | string | (No unit) | 3062 | 142398 |
| 5 | Rain Today | 'Yes' if it rains today. 'No' if not raining today. | Yes, No | Total 3261 | string | (No unit) | 3261 | 141851 |
| 6 | Rain Tomorrow | If it rains tomorrow, then 1 (Yes). If it doesn't rain tomorrow, then 0 (No). | Yes, No | Total 3267 | string | (No unit) | 3267 | 142193 |

TABLE V. TUPLES OF HIGHLY POSITIVELY AND STRONGLY CORRELATED FEATURES IN OVERALL CONTINENT

| No | Tuple | Correlation Coefficient |
|---|---|---|
| 1 | The attributes Max and Min temperatures have a significant positive correlation. | 0.74 |
| 2 | There is a significant positive link between the minimum temperature and the temp3pm. | 0.71 |
| 3 | The attribute 9am temperature and Min Temp are strongly positively correlated. | 0.90 |
| 4 | Max Temperature and Temp 9am exhibit a strong positive association. | 0.89 |
| 5 | Maximum temperature and temperature at 3 p.m. are both fairly high. | 0.98 |
| 6 | Wind Gust Speed and WindSpeed3pm variables are highly positively correlated. | 0.69 |
| 7 | Pressure 9am and Pressure 3pm variables are strongly positively correlative. | 0.96 |
| 8 | The variables Temp 9am and Temp3pm have a high positive correlation. | 0.86 |

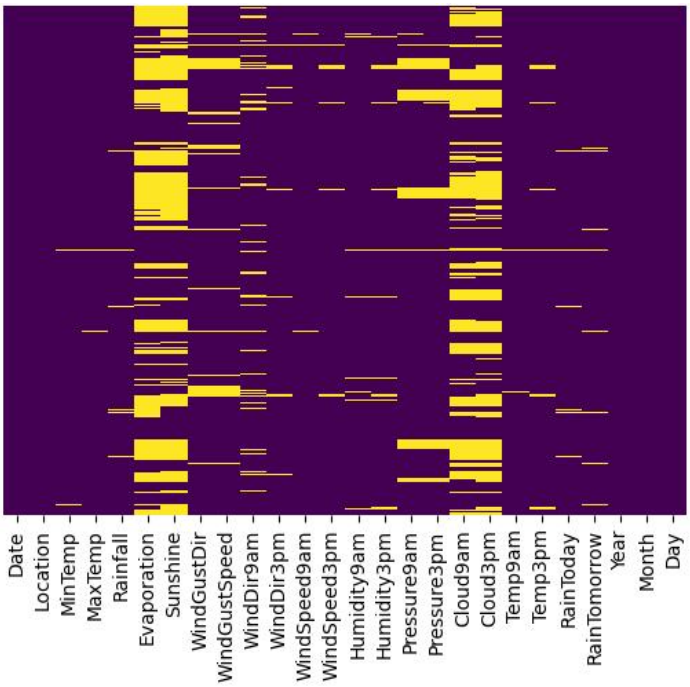


Fig. 2. Visual representation of missing values for each feature in the dataset.

are predominantly in different parts of Australia. The earlier study made use of a dataset that had a large number of cities. There are data gaps in several cities. For this reason, consider the following five Australian research regions((Darwin, Perth Airport, Sydney, Brisbane, and Melbourne). Given the aforementioned and the fact that local weather patterns and microclimates can frequently differ greatly, especially when taking into consideration weather forecasts for the entire continent, it should be more sensible to construct unique models for various locations. As a result, this study produces weather predictive models for various areas. To comprehend the numerous factors that affect whether it rains the following day, this study consider each city's specific model separately. In this study, it was also investigated whether applying machine learning and deep methods may help with rainfall predictions in this particular Australian location. Fig. 5 shows the locations of five Australian cities (Drawn, Perth Airport, Sydney, Brisbane, and Melbourne).

Fig. 6 displays the city-specific rain forecast for tomorrow. Fig. 7 shows that the month has less of an impact on the distribution of rainy days in Sydney and Melbourne. However, count plots for Brisbane, Perth, and Darwin indicate that these locations experience both wet and dry months (particularly Darwin).Darwin had more wet days than Perth did over the course of the research period, even though the count plot indicates that there are much more days with rain than days without

In particular, this study will be used to find out whether the application of deep learning and machine learning algorithms can lead to a higher precision grade and a drop in errors.. Everyone who is now alive in the country will gain something from this endeavor.Four machine learning methods are used in the suggested method to forecast rainfall Random Forest(RF), Gradient boosting (GB) etc. The framework incorporates a number of crucial processes, pre-processing, data normalization and feature engineering including feature selection, feature encoding, model training, and prediction evaluation. The proposed work involves the optimization of a classification model for the rain prediction with the help of supervised machine learning (ML) and deep learning(DL) methods. The primary objective of the research is to achieve maximum accuracy in rainfall prediction. This objective is pursued through the application of supervised learning and deep learning methodologies. The methodology revolves around supervised learning, where the model learns patterns from labeled training data. Specifically, deep learning is highlighted, resulting in the application of multiple layer neural networks that exhibit an ability to capture complicated patterns in the data. Fig. 8 indicates the overall framework of the proposed scheme for forecasting precipitation. It may illustrate the different components of the model, such as data preprocessing, feature extraction, model training, and evaluation. The architecture of the proposed research work is presented in Fig. 8.

*1) Data cleaning and pre processing missing data:* Another significant part of data preprocessing in machine learning generally is management of missing data in a dataset. Fig. 2 demonstrates the number of blank samples available for two variables. Through a total of 145,460 samples, for 23 variables.Therefore, nearly 45% of the samples would need to be deleted if the samples with no data for any of their variables were also eliminated. In order to avoid throwing away a lot of data(there are a total of 49 cities dataset contain ) e. g [‘albury’ ;‘Badgerys Creek’ ,‘cobar’ ;‘coffs harbor’ ‘moree’ ‘Newcastle’; ‘Norah Head’; ‘Norfolk Island’; ‘penrith’ ‘Richmond’ ,‘Sydney’ ,‘Sydney Airport’ ‘waggaWagga’ ,‘Williamstown’ ,‘Wollongong’; ‘Canberra’ ‘Tuggeranong’; ‘mount_Ginini’ ,‘ballarat’ ,‘bendigo’, ‘Sale’ ‘Melbourne AirPort’ ‘Melbourne’; ‘Mildura’; ‘nhil’ ,‘Portland’;‘Watsonia’; ‘Dartmoor’ ,‘Brisbane’ ‘cairns’, ‘gold Coast’ ;‘Townsville’ ,‘Adelaide’ ,‘mount Gambier’ ,‘nuriootpa’ ,‘woomera’, ‘Albany’,;‘Witchcliffe’ ,‘Pearce’ ).

In total, seven (7) different stations in the dataset. In particular, less than 10 percent of string text data is missing or absent. The variables that lacked data were examined and categorized according to the cities. The examination of factors for which there are data produced the following results. In some of the cities, certain parameters do not have any data at all. There are samples for which certain variables have no information. It is assumed that this is due to a lack of a corresponding sensor at the city's weather site or data not recorded. A malfunction in the sensors' communication with each other could be the reason. As with the previous case, two different scenarios were shown to exist: data loss for one day and data loss for several days in a row [16]. It was decided to remove all null values for all features in this case. Using only 41% of observations is possible. Detecting and removing outliers from the dataset finally, in the case of objective variables, In this work balance the imbalance data. Fig. 9 and Fig. 10 depict the balance and imbalance target variable.

*2) Data normalization:* Scaling variable values to give them the same quantitative weight and place them on the same interval or scale is known as data normalization. Rescaling the

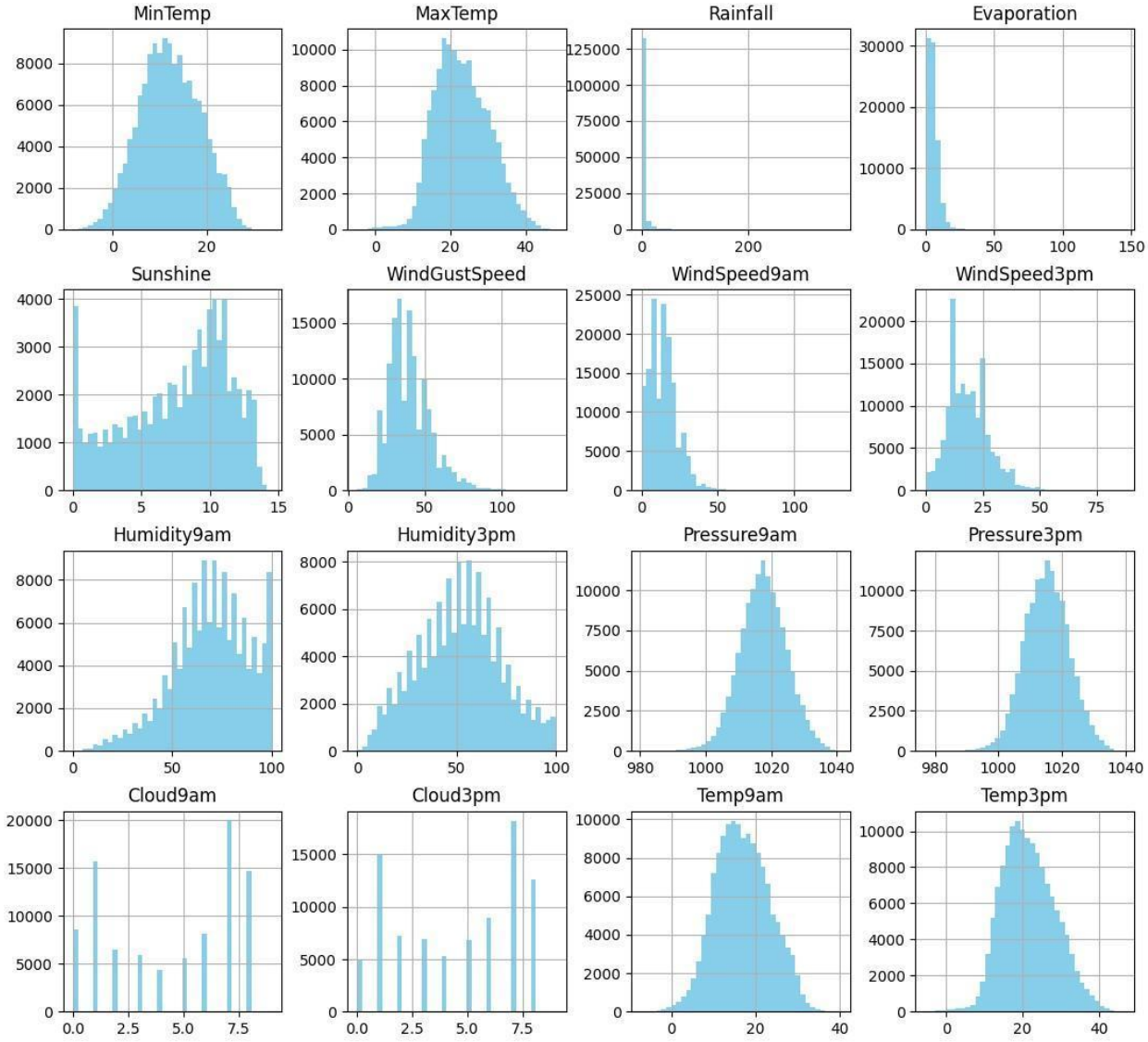


Fig. 3. Histogram showing the dataset's attribute statistics.

complete dataset to a standard distribution or range. Eq. (1) provides a method for normalizing data using the min-max scaling strategy.

$$x_{(normalized)} = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

Where: x stands for the dataset's original value, min(x) for its lowest value, max(x) for its highest value, and x_normalizedfor its normalized value falls between 0 and 1. The values of the complete dataset are scaled by Eq. (1) to the range [0, 1], where the smallest value is made to equal 0 and the largest value is produced to equal 1.

*3) Feature engineering:* First, the map reveals that Watsonia, Perth, and Melbourne airports are all close to one another. Based on this, assume that it makes sense to select Melbourne and Perth airports for rain prediction because they have fewer null variables than Watsonia and Perth. Although the date field itself does not contain any meteorological information, it is possible to get the month and utilize it to study weather patterns. In this experiment, the month feature that had been removed is replaced by (January, February, March, April, May, June, July, August, September, October, November and December). Since the data in the region as a whole had to be investigated, the data pertaining to each place has not been divided to create distinct subsets. For instance, there are some cities with heat and humidity circumstances that more or less favor rain, based on their location. Similarly, on the day the data is collected, several weather events may take place that affect the rain.

*4) Feature encoding:* In our dataset some features are categorical and some numerical. The category variables were then converted into numerical values. Two distinct sets of data variables had to be used in this process On the other hand, because the parameters WindGustDir, WindDir9am, and WindDir3pm show the direction of the wind, the data transform

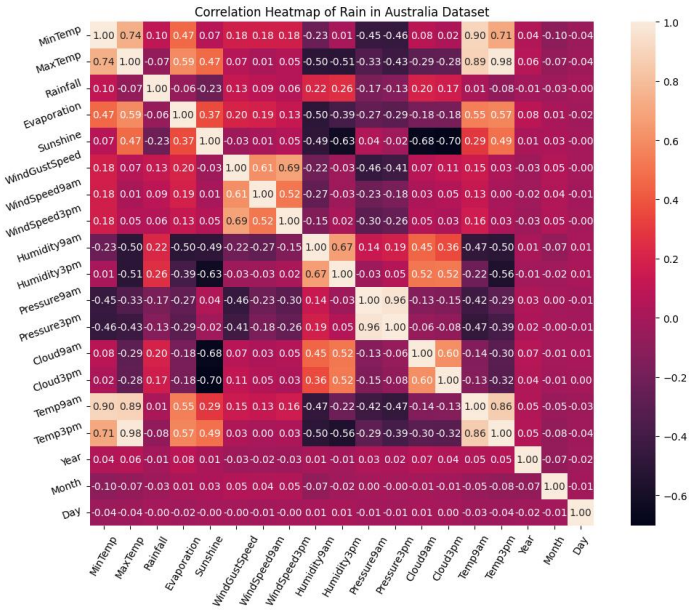


Fig. 4. Correlation with variables.

into numeric form before using them because they contain a categorical data string. Our study's goal variable is called Rain Tomorrow, and its values of "1, 0" are applied to Boolean representations of type "string" (which only take YES/NO responses). Fig. 4 shows correlation with variables.

*5) Feature scaling:* The process of scaling individual features within a dataset to have comparable magnitudes is known as feature scaling. The Standard Scalar was used to scale the dataset's features in order to guarantee that it was equitable and appropriate for the models that were used. The data are scaled by placing a unit standard deviation around the mean. The feature scaling using the z-score scaling or standardization technique is represented in Eq. (2). The feature scaling takes place element wise and for every feature.

$$x_{(Scalled)} = \frac{x - \mu}{\theta} \tag{2}$$

Where: x indicates the feature's original value, is the dataset's mean (average), is the feature's standard deviation, and ,The scaled value of the feature, x_scaled, has a standard deviation of 1 and a mean of 0. Eq. (2) is applied to alter the attribute values to have a mean of 0 and a standard deviation of 1.

*6) After preprocessing result:* A total of 145460 samples were collected over a ten-year period in 49 Australian cities for the initial set of variables, which included 23 ('Date', 'Min Temp', 'Max Temp', 'Rainfall', 'Evaporation', 'Sunshine', 'Wind Gust Speed', 'Wind Speed 9am', 'Wind Speed 3pm', 'Humidity 9am', 'Humidity 3pm', 'Pressure 9am', 'Cloud 9am', 'Cloud 3pm', 'Temp 9am', 'Temp 3pm', 'Location', 'Wind Gust Dir', 'Wind Dir. 9am', 'Rain Today', 'Rain Tomorrow', 'Pressure 3pm',. Unlike Salvia Main, the site's dataset is made of 79 columns, resulting in a total of 14 727 samples. In addition to that, approximately 80% of the data gathered out of these 14727 samples is used for training the models and remaining 20% of the data is used for checking the functioning of the newly developed models.

In the present Australia rainfall prediction, the integration of some basic normalization methods such as min-max scaling and z-score standardization enhance the model prediction. Most of the rainfall prediction models involve various properties such as temperature, humidity and wind speed, all of which have different units and scales. Scaling makes sure that all different features are equally important, thus their values are transformed into the same range. This restricts the longer feature space ranges from becoming dominant over other small feature space ranges and aids in learning algorithms like neural networks and Decision Tree learn faster and better during the training process. Normalization also enhances numerical stability and prevents the model from having a bias towards features with large variances, thus enhancing the accuracy of the rainfall estimation.

## IV. Results

Using the location segment, for analyzing and dividing the dataset into various regions so that it could create a variety of unique models, Fig. 7 represents the different locations of Australia. To see the differences between the causes triggering rain on subsequent days, analyze the models independently. Machine learning (ML) techniques have considerably improved prediction systems over the past two decades by offering more efficient and approachable means of replicating the intricate mathematical representations of the physical processes causing floods. Analyzing the possibilities that machine learning and deep learning algorithms offer to conventional forecasting methodologies for the prediction of rain is the aim of this study. This was accomplished using the techniques of neural networks (NN), Decision Tree (DT), Random Forests (RF), and Gradient Boosting Classifiers (GBC). Examine the benefits of rainfall probability in Australia's five biggest cities: Darwin, Sydney, Brisbane, Perth, and Melbourne, using the methodology given.A more detailed description of the algorithms may be found below. The values from the training dataset have been predicted by using a specific location.

*1) Decision tree:* Using a Decision Tree machine learning approach [60]–[62], problems with regression and classification are addressed. Its organization is comparable to a flowchart, where a decision rule is represented by each branch, an attribute or characteristic by each internal node, and a result or class label by each leaf node.

*2) Random forest:* During training, a massive number of decision trees are constructed by an ensemble learning system known as Random Forest [62], which then outputs the average forecast for regression tasks or the majority vote for classification tasks. Random Forest is resistant to over fitting and performs well on a variety of datasets. It can handle missing values and remain accurate even with a large feature set. The Random Forest approach is depicted in Fig. 11

*3) Gradient boosting classifier:* A powerful ensemble learning method for classification and regression applications is gradient boosting. Gradient Boosting constructs Decision Tree sequentially, with each tree learning from the mistakes of its predecessors, in contrast to typical decision tree algorithms like Random Forest, which generate many trees individually


Fig. 5. Geographical location of five specific regions of Australia.


Fig. 6. Tomorrow's forecast for a specific city.

[63] as shown in Fig. 12. Initialize the model with a simple model, such as a single leaf (constant) value for regression or a constant probability for classification. Then it calculates the residuals or pseudo-residuals for each data point, which represent the errors made by the initial model.

$F_m((x)$ as the current ensemble model (sum of first m weak learners) $h_m((x)$ as the m-th weak learner (e.g., Decision Tree ), Φ as the learning rate, L as the loss function. At each iteration, update the model as follows:

At each iteration, update the model through Eq. (3) as follows:

$$F_m(x) = F(-1)(x) + \rho \cdot h_m(x) \tag{3}$$

Then, the residuals (or pseudo-residuals) are updated the Eq.4:

$$r_{im} = \frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)} \tag{4}$$

Finally, the prediction at each iteration is given by Eq. 5:

$$y_{\text{pred}}(x) = F_M(x) = \sum_{m=1}^{M} \rho \cdot h_m(x) \tag{5}$$

*4) Recurrent Neural Network:* Recurrent Neural Networks (RNNs), on the other hand, serve as the foundation for sequential data processing within neural networks. These architectures operate iteratively through sequences, updating hidden states at each step to encapsulate contextual information. However, RNNs often encounter challenges when attempting to retain information over prolonged sequences, commonly referred to as the vanishing gradient problem. Despite their limitations, RNNs remain widely used for various sequential data tasks, such as language modeling, sentiment analysis, and machine translation. While they may struggle with long-term dependencies, RNNs offer simplicity and computational efficiency, making them suitable for applications where shorter-term relationships are predominant.

The RNN's computations are governed by the following formulas. Eq. (6) is utilized in the computation of hidden states:

The function $h(t)$ is calculated as follows:

$$h(t) = f\left(W_{xh} \cdot x(t) + W_{hh} \cdot h(t-1) + b_h\right) \tag{6}$$

Eq. (6) is used for output calculation:

$$y(t) = f\left(W_{hy} \cdot h(t) + b_y\right) \tag{7}$$

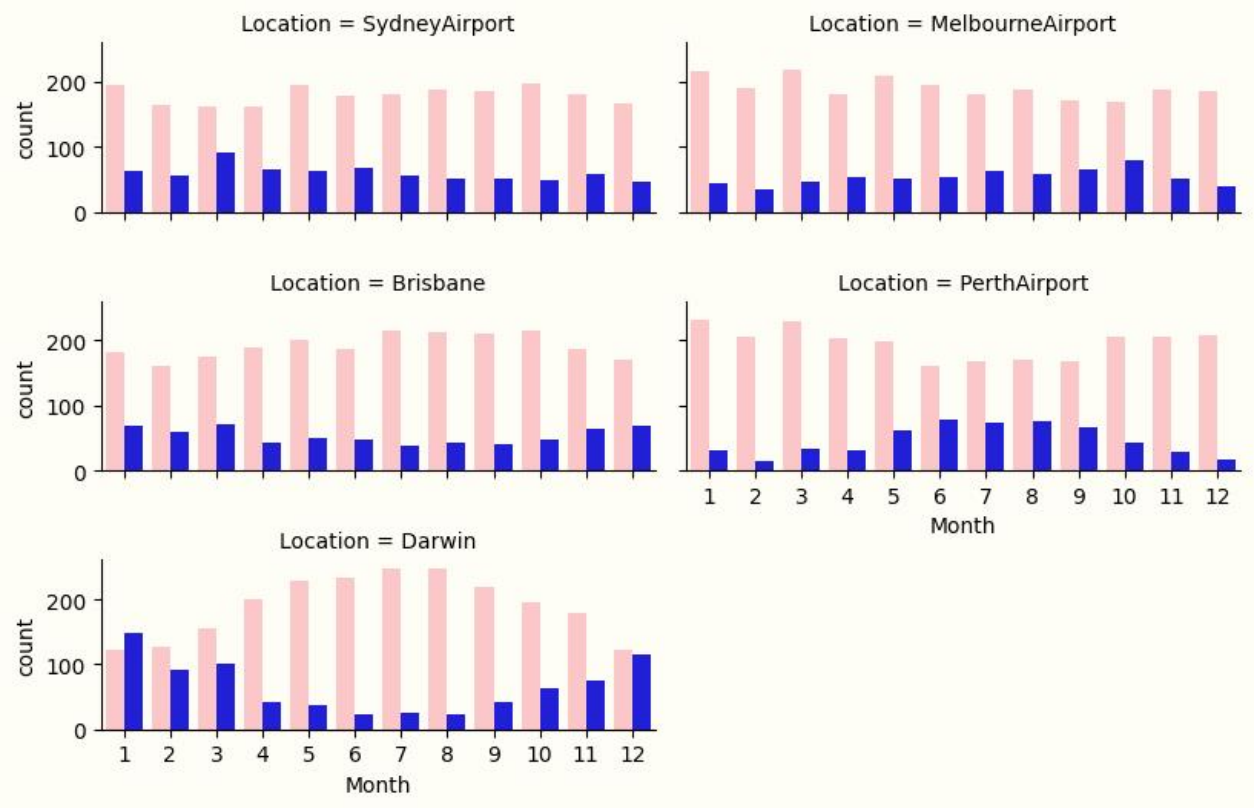


Fig. 7. Tomorrow's forecast for a specific city.

Where $t$ is the time step, $x(t)$ is the input at time step $t$, and $h(t)$ is the hidden state at time step $t$. The weight matrices $W_{xh}$ and $W_{hh}$ control the flow of information, and $b_h$ and $b_y$ are bias vectors.

The following equations are used for the input gate:

$$i(t) = \text{sigmoid}\left(W_i \cdot [h(t-1)\, x(t)] + b_i\right) \tag{8}$$

The candidate cell state $\hat{C}(t)$ is computed as:

$$\hat{C}(t) = \tanh\left(W_c \cdot [h(t-1)\, x(t)] + b_c\right) \tag{9}$$

The cell state updating function is given by:

$$c(t) = f(t) \cdot c(t-1) + i(t) \cdot \hat{C}(t) \tag{10}$$

The output gate computations are as follows:

$$o(t) = \text{sigmoid}\left(W_o \cdot [h(t-1)\, x(t)] + b_o\right) \tag{11}$$

Finally, the hidden state is calculated as:

$$h(t) = o(t) \cdot \tanh\left(c(t)\right) \tag{12}$$

### A. Criteria for Evaluating Models

The metrics (or key indicators of performance (Key Performance Factors)) that will be used to evaluate the algorithms' output are described in this section [64].

*1) Accuracy:* Number reflecting how well the predicted model performed. The formula shown in Eq. (13)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \tag{13}$$

Where, TP designates it as "true positives." "Result where the model outputs a positive class and correctly classifies it. FP is called a False Positive. Lead to a case in which the positive class is erroneously designated by the model as a negative class. TN, or the true negative, connotes the outcome where the model predicted the negative class to be. False negative, i.e. FN is a concept in detection that is associated with negative. is a situation where the model predicts the other class to be wrong.

*2) Precision:* The percentage of instances that are correctly identified as positive is known as precision. Which is, whether a model forecasts positive numbers. The formula shown in Eq. (14).

$$\text{Precision} = \frac{TP}{TP + FN} \tag{14}$$

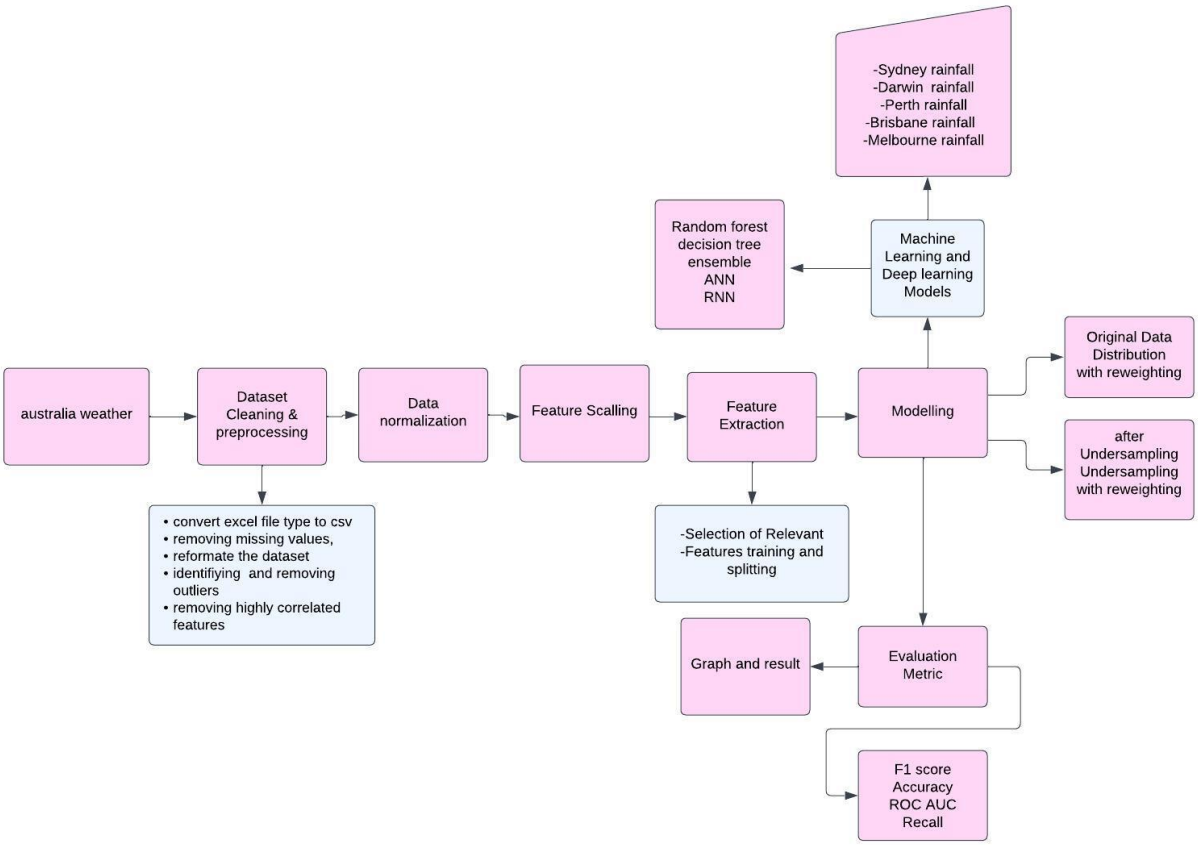


Fig. 8. Architecture of the proposed work.

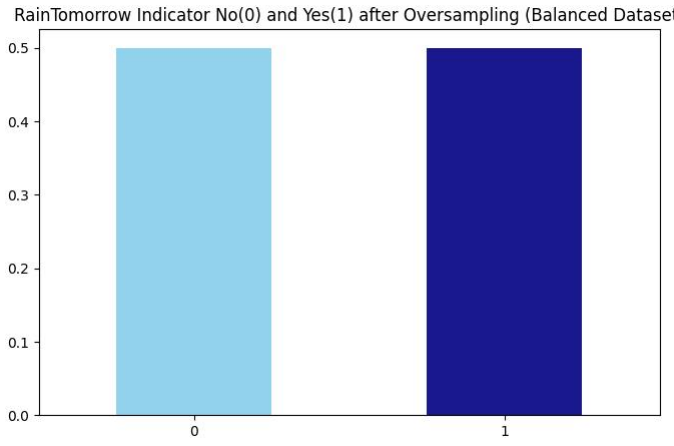


Fig. 9. Rain tomorrow indicator no(0) and yes(1) after oversampling (balanaced dataset).

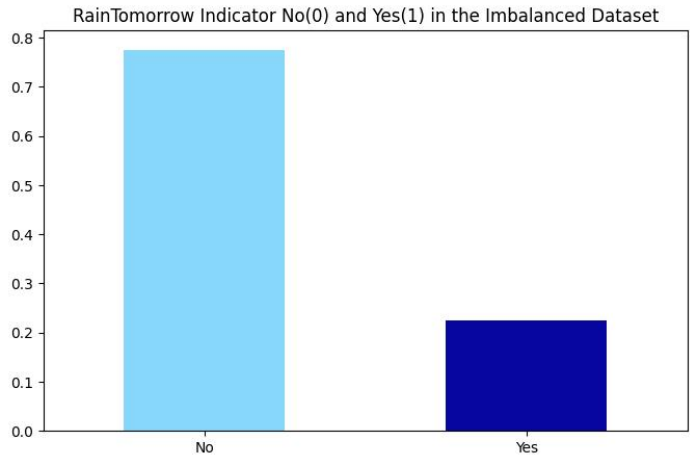


Fig. 10. Rain tomorrow indicator no(0) and yes(1) in the imbalanaced dataset.

*3) Recall:* The percentage of correctly detected positives to all positives is known as recall. The sensitivity formula and this formula are identical as shown by Eq. (15).

$$\text{Recall} = \frac{TP}{TP + FP} \tag{15}$$

*4) F1 score:* When precision and recall are insufficient for evaluating performance, for as when one mining method has better accuracy but worse recall than another, the question of which algorithm is superior may come up. The F-measure, which gives the mean of recall and precision, can be used to address this problem. An industry standard for evaluating

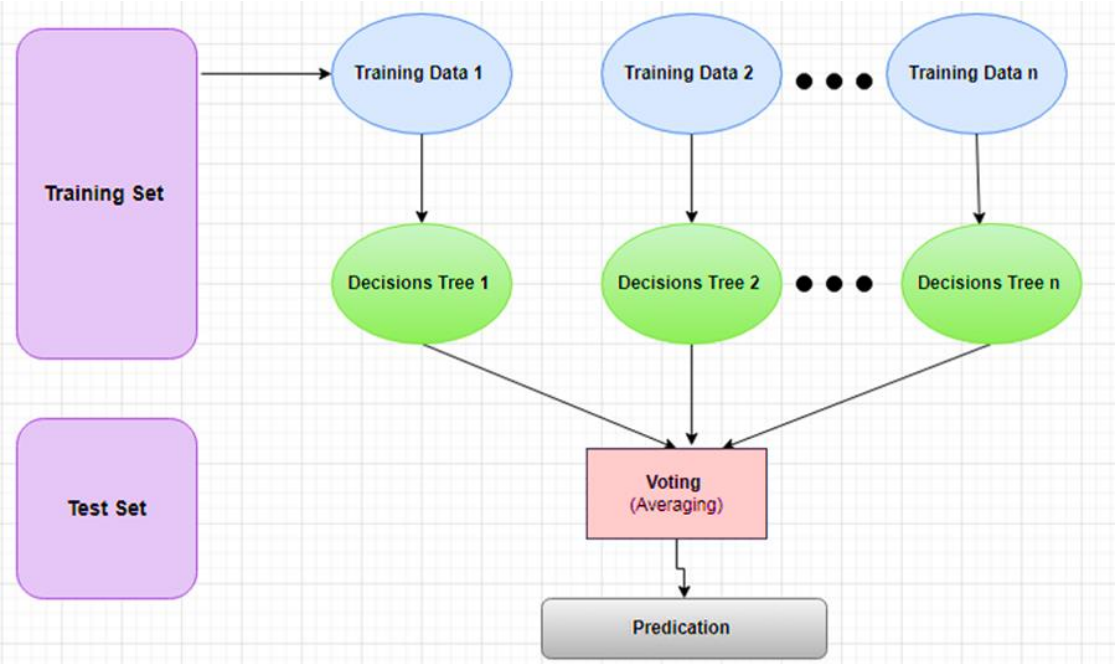


Fig. 11. Representation of random forest algorithm.

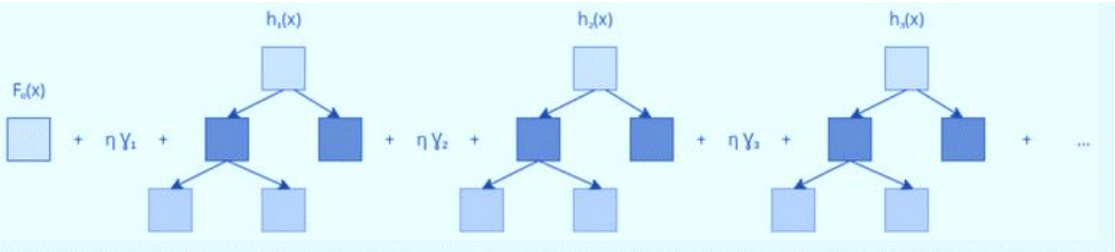

Fig. 12. Representation of gradient boosted trees.

the performance of a classification model is the F1 score. Eq. (16) shows how the computation appears. It provides an equitable evaluation of a model's accuracy by merging recall and precision into a single metric.

$$\text{F1 score} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{16}$$

*5) ROC AUC:* AUC ROC stands for areas under the curve of the "Receiver Operating Characteristics" curve. The performance of an ML model is commonly assessed using the AUC ROC curve. The ROC curve's AUC definition measures how well a binary classifier can differentiate between different categories.

## B. Experimental Results

Due to the fact that factors affect rainfall in different regions differently, it is impossible to produce a model that would be able to predict rainfall across the whole Australia. Models can be constructed only for restricted areas to know what roles with probability of rain are the variables being assigned. The data set contains daily weather observations from several locations in Australia for about 10 years. The impact of the data's location was examined in this experiment. The data in this set includes around ten years' worth of daily weather observations made in various parts of Australia. However, This study concentrated on five specific cities (Perth Airport, Malbulane, Brisbane, Sydney, and Darwin) for the objectives of our study. In order to predict whether it would rain on a certain day, machine learning methods were tried on the Rain Tomorrow feature.

*1) Sydney decision tree results:* Table VI presents Sydney result using Decision Tree.

Table VI represents the model's result with the initial data and the undersampling. It can be said that the results of the Random Forest and Gradient Boosting classifiers are very near to each other with the Decision Tree and Ensemble classifiers as shown in Table VII. In this study Random Forest and Gradient boosting models are built using undersampling and assume that the RF classifier, given its somewhat superior performance, is the best model for the dataset.

Table VI presents Sydney Comparison of all results By using Random forest and Gradient Boosting.

TABLE VI. SYDNEY RESULT USING DECISION TREE

| Metric | Original Data Distribution | Original Data Distribution with Reweighting | Under Sampling | Under Sampling with Reweighting |
|---|---|---|---|---|
| **Accuracy** | 0.83 | 0.78 | 0.77 | 0.70 |
| **F1 score** | 0.60 | 0.60 | 0.61 | 0.58 |
| **ROC_AUC** | 0.72 | 0.75 | 0.75 | 0.74 |
| **Recall class 1** | 0.50 | 0.69 | 0.71 | 0.84 |

TABLE VII. SYDNEY COMPARISON OF ALL RESULTS USING RANDOM FOREST AND GRADIENT BOOSTING

| Metric | Original Data Distribution | Original Data Distribution with Reweighting | After Under Sampling | Under Sampling with Reweighting | Random Forest | Gradient Boosting |
|---|---|---|---|---|---|---|
| **Accuracy** | 0.83 | 0.78 | 0.77 | 0.70 | 0.79 | 0.78 |
| **F1 score** | 0.60 | 0.60 | 0.61 | 0.58 | 0.64 | 0.64 |
| **ROC_AUC** | 0.72 | 0.75 | 0.75 | 0.74 | 0.78 | 0.77 |
| **Recall class 1** | 0.50 | 0.69 | 0.71 | 0.84 | 0.76 | 0.76 |

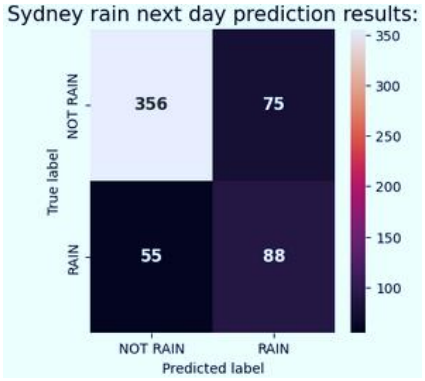


Fig. 13. Sydney next day prediction result.

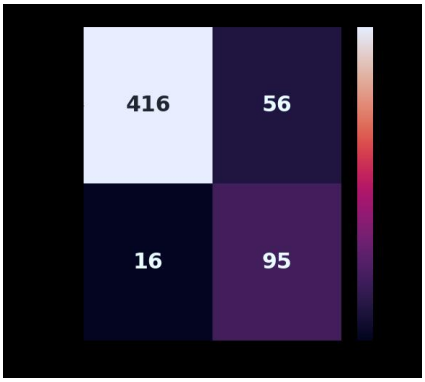


Fig. 14. Perth airport next day prediction result.

### C. Perth Airport, Brisbane, Melbourne, Darwin Comparison Accuracy using ML Algorithm

Building a model that can forecast rain for the entire Australian continent is unachievable because different factors have varying effects depending on where they are. Only for specific areas models build and look at how the variables affect the probability of rain. In this study created models for specific locations and examined the variables' effects on the likelihood of rain. Without comparing it to a single tree, Random Forest model with under sampled training data is the best choice for Perth Airport, Brisbane, Melbourne, Darwin. Table VIII represents the prediction result for all 5 locations of Australia and also shows us that it's possible to predict rain for next day with different accuracy depending on the location (using one model type - RF classifier).

The confusion matrix of five specific regions of Australia for rainfall prediction are presented in Fig. 13, 14, and 15.

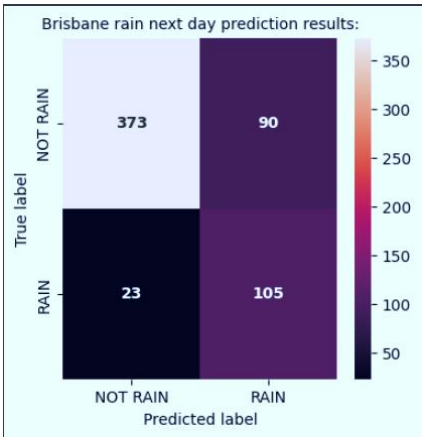


Fig. 15. Brisbane next day prediction result.

### D. Estimation of Feature Importance

The estimation of feature importance for different cities is presented in this subsection as follows:

*1) Estimation of feature importance for Sydney:* Here only a couple of weather factors affect Sydney weather. The main factors are sunshine, wind speed 3 p.m., humidity 3 p.m., maximum temperature, air pressure 9 a.m. and air pressure 3 p.m. TableIX provides Feature Importance for Sydney. All other features have importance less than 1 percent.

*2) Estimation of feature importance for Perth airport:* The most essential factors causing rain next day in Perth (Airport) are Pressure 3pm, Pressure 9am, Wind Gust Speed, Evaporation, Wind Speed 3pm, Sunshine, Rainfall. Table IX describe some factors with F1 score. Table X provides Feature Importance for Perth Airport city. All other features have importance less than 1 percent.

*3) Estimation of Feature Importance for Brisbane city:* The key elements causing rain the following day in Brisbane are the following: humidity, 3 p.m. sunshine, humidity, 9 p.m.,

TABLE VIII. PREDICTION RESULTS FOR ALL 5 LOCATIONS OF AUSTRALIA USING RANDOM FOREST

| Metric | (i) Sydney | (ii) Darwin | (iii) Perth | (iv) Brisbane | (v) Melbourne |
|---|---|---|---|---|---|
| **Accuracy** | 0.79 | 0.86 | 0.88 | 0.82 | 0.76 |
| **F1 score** | 0.64 | 0.76 | 0.73 | 0.66 | 0.58 |
| **ROC AUC** | 0.78 | 0.87 | 0.87 | 0.82 | 0.76 |
| **Recall** | 0.76 | 0.89 | 0.86 | 0.81 | 0.77 |

TABLE IX. FEATURE IMPORTANCE FOR SYDNEY

| Feature | Sunshine | Wind Gust Speed | Humidity 3pm | Wind Speed 3pm | Max Temp | Pressure 9am | Pressure 3pm |
|---|---|---|---|---|---|---|---|
| **F1 Score** | 0.04 | 0.02 | 0.018 | 0.017 | 0.014 | 0.014 | 0.013 |

TABLE X. FEATURE IMPORTANCE FOR PERTH AIRPORT CITY

| Feature | Pressure 3pm | Pressure 9am | Wind Gust Speed | Evaporation | Wind Speed 3pm | Sunshine | Rainfall |
|---|---|---|---|---|---|---|---|
| **F1 Score** | 0.06 | 0.04 | 0.03 | 0.021 | 0.014 | 0.013 | 0.01 |

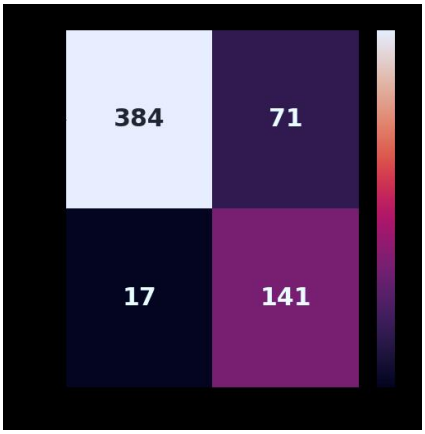


Fig. 16. Darwin next day prediction result.

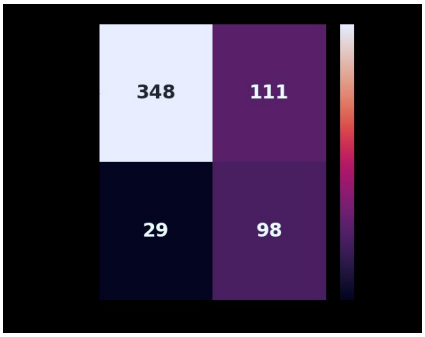


Fig. 17. Melbourne next day prediction result.

clouds, maximum temperature, 9 a.m., minimum temperature, and pressure at 3 p.m. Table IX outlines the F1 score-related elements. Table XI provides Feature Importance for Brisbane. All other features have importance less than 1 percent.

*4) Estimation of feature importance for Darwin city:* The most essential factors causing rain next day in Darwin are Humidity 3pm, Wind Gust Speed, sunshine,Temp 3pm. Table 9d describe some important attribute with F1 score. Table XII provides feature importance for Darwin. All other features have importance less than 1 percent (Pressure 3pm, Min Temp, Rainfall, Wind Speed 9 am, Wind speed) (see Fig. 16).

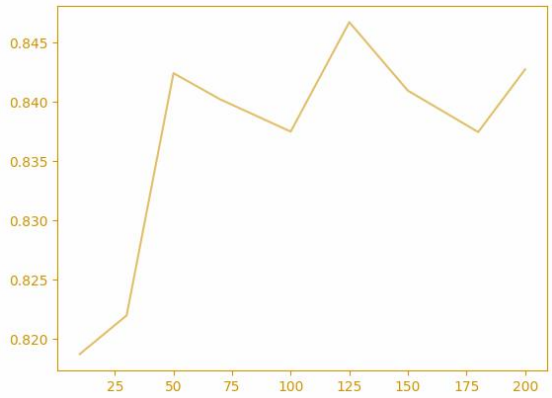


Fig. 18. Darwin ROC curve representation.

*5) Estimation of feature importance for Melbourne airport city:* Through extensive research, three notable factors in determining the rain tomorrows forecast for Melbourne (Airport) – Humidity 3pm, Sunshine, Pressure 3pm – were discovered. Table IX describe the f1 score of these important features. Table XIII provides Feature Importance for Melbourne Airport. All other features have importance less than 1 percent (see Fig. 17).

### *E. Ranking of the Most Significant Elements for Various Locations*

After modeling, feature importance was analyzed, and the feature importance boxplot shows that certain models with poor outcomes might have been over fitted. Table XIV provides ranking of the most important factors for different regions. The table further shows that the most important variables at various locations are air pressure, air humidity, wind gust speed, and wind speed.

It seems like a good idea to gather more information on these qualities for each area and to keep better track of variables like clouds, sunshine, temperature, and so forth depending on the location. Fig. 18 to 22 represent the curve result of the cities.

TABLE XI. FEATURE IMPORTANCE FOR BRISBANE

| Feature | Humidity 3pm | Sunshine | Humidity 9pm | Cloud 3pm | Max Temp | Temp 9am | Min Temp | Pressure 3pm |
|---|---|---|---|---|---|---|---|---|
| **F1 Score** | 0.07 | 0.023 | 0.016 | 0.016 | 0.013 | 0.012 | 0.012 | 0.011 |

TABLE XII. FEATURE IMPORTANCE FOR DARWIN

| Feature | Humidity 3pm | Wind Gust Speed | Sunshine | Temp 3pm |
|---|---|---|---|---|
| **F1 Score** | 0.037 | 0.03 | 0.0185 | 0.01 |

TABLE XIII. FEATURE IMPORTANCE FOR MELBOURNE AIRPORT

| Feature | Humidity 3pm | Sunshine | Pressure 3pm | Cloud 9am | Pressure 9am | Wind Gust Speed | Wind Speed 3pm | Temp 3pm | Max Temp |
|---|---|---|---|---|---|---|---|---|---|
| **F1 Score** | 0.036 | 0.03 | 0.025 | 0.019 | 0.017 | 0.016 | 0.014 | 0.01 | 0.01 |

TABLE XIV. RANKING OF THE MOST IMPORTANT FACTORS FOR DIFFERENT REGIONS

| Rank | Sydney | Darwin | Perth Airport | Brisbane | Melbourne Airport |
|---|---|---|---|---|---|
| **1** | Sunshine | Humidity 3pm | Pressure 3pm | Humidity 3pm | Humidity 3pm |
| **2** | Wind Gust Speed | Wind Gust Speed | Pressure 9am | Sunshine | Sunshine |
| **3** | Humidity 3pm | Sunshine | Wind Gust Speed | Humidity 9am | Pressure 3pm |
| **4** | Wind Speed 3pm | Temp 3pm | Evaporation | Cloud 3pm | Cloud 9am |
| **5** | Humidity 9am | Pressure 3pm | Wind Speed 3pm | Max Temp | Pressure 9am |

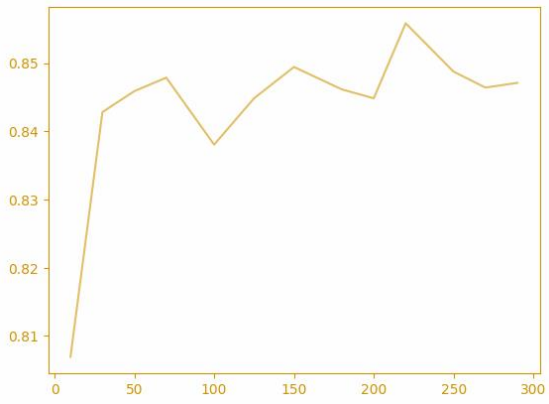


Fig. 19. Perth Airport ROC curve representation.

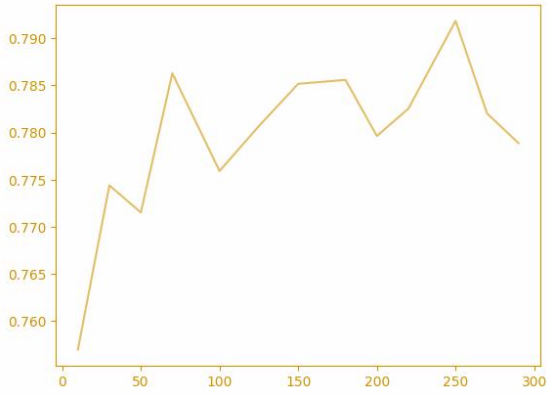


Fig. 20. Brisbane ROC curve representation.

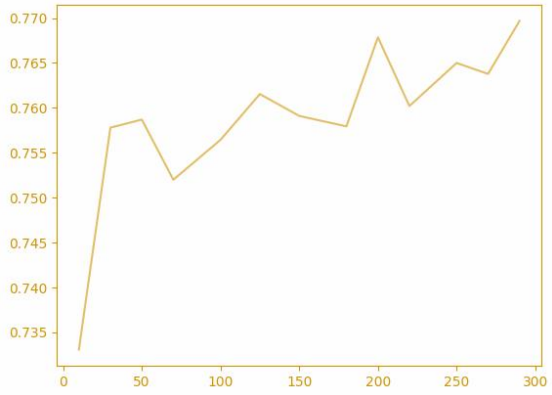


Fig. 21. Melbourne airport ROC curve representation.

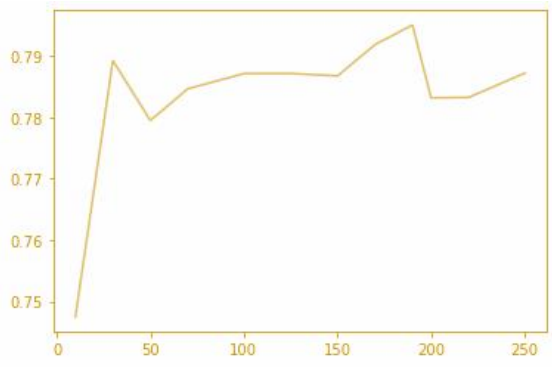


Fig. 22. Sydney ROC curve representation.

```
Model: "sequential_17"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn_14 (SimpleRNN)   (None, 100)               10200

 dropout_14 (Dropout)        (None, 100)               0

 dense_14 (Dense)            (None, 1)                 101

=================================================================
Total params: 10,301
Trainable params: 10,301
Non-trainable params: 0
_________________________________________________________________
```

Fig. 23. RNN Model configuration.

### F. Perth Airport, Brisbane, Melbourne, Darwin Accuracy using Recurrent Neural Network

Fig. 23 presents the default architecture of the RNN network that was applied. The table shows the RNN model efficacy in Table XII below. The parameters are displayed in Table XV for the Creation of DL model, as shown below. This table provides parameter value used for training.

TABLE XV. PARAMETER VALUES USED FOR TRAINING

| Parameter | Values |
|---|---|
| **Epochs** | 150 |
| **Batch Size** | 256 |
| **Learning Rate** | 0.0003 |
| **Optimizer** | Adam |
| **Loss** | Binary Cross Entropy |
| **Metrics** | Accuracy |

This study makes use of a unique, three-layer ANN model. Assess and assemble the model using 150 epochs. Adam Optimization used in this experiment with a batch size of 256. Table XVI provides five cities Result by using RNN and compares Darwin's validation loss to others and shows that it is better. And the graph shows that loss in training and testing both rapidly lowers as the number of epochs rises. Fig. 24 to Fig. 28 shows the loss over iterations for RNN model of five city of Australia (Sydney, Darwin, Perth airport, Brisbane, Melbourne airport.

## V. COMPARISON OF RESULTS WITH EXISTING FLOOD AND RAINFALL PREDICTION METHODS

Our applied model outperformed several well-known algorithms across various locations, showing notable accuracy gains. For example, the Random Forest model used in our study achieved an accuracy of 0.83 for Sydney, which is higher than the 0.78 accuracy reported in other studies using comparable datasets. Additionally, we obtained a validation loss of 0.5523 for Sydney with our Recurrent Neural Network (RNN) methodology, which is significantly lower than the losses reported in previous approaches, ranging from 0.63 to 0.71. Furthermore, our proposed machine learning approach not only matched but also exceeded the results of prior studies on flood prediction in Bangladesh, where logistic regression had an accuracy of 0.8676. Previous studies had primarily employed advanced techniques like reweighting and undersampling to enhance performance on imbalanced datasets. Overall, the results of our study demonstrate a significant improvement in the ability to predict floods and rainfall, proving the efficacy of our approach compared to earlier research.

## VI. NOVELTY OF THE PROPOSED METHODOLOGY

The proposed method is novel as it combines the structural assignment method with the use of a spin-glass model. This work introduces a Rainfall Forecasting Model that leverages state-of-the-art artificial intelligence and machine learning techniques, specifically employing Recurrent Neural Networks alongside advanced machine learning algorithms. The novelty of our approach lies in the following aspects:

### A. Integration of RNNs

Unlike most other studies that primarily focus on classical machine learning approaches or simpler RNN structures, this study leverages RNNs. This choice enables the model to capture temporal dependencies present in rainfall data. RNNs are particularly useful for processing sequential data, making them well-suited for forecasting models where past observations strongly influence future values.

### B. Comparative Analysis with Diverse Algorithms

In addition to comparing it with other deep learning models, we also evaluate RNN against traditional machine learning methods, including Random Forest (RF), Decision Tree (DT), and Gradient Boosting Classifier (GBC). This comprehensive cross-comparison reveals the relative advantages and disadvantages of each method in forecasting rainfall, providing valuable insights into their performance.

### C. Feature Importance Ranking

This study not only performs algorithmic comparisons but also provides a combined analysis and ranking of key meteorological factors across various regions. This analysis helps explain why, despite similar overall causes, different variables influence the amount of rainfall in various cities across Australia.

### D. Undersampling with Reweighting

We adopt undersampling with reweighting procedures to address the class imbalance problem in our dataset, which is common in precipitation forecasting. This method improves the accuracy of our predictions by ensuring that minority classes, such as instances of high rainfall occurrence, are given adequate weight and not overlooked due to their rarity.

### E. Improved Accuracy and Reliability

In this study, after addressing the class imbalance, this approach improves prediction accuracy by ensuring that minority classes, such as cases of high rainfall, receive appropriate weight during model training. As a result, rare but significant occurrences are not overlooked, leading to more reliable and accurate rainfall predictions.

TABLE XVI. FIVE CITIES RESULT USING RNN

| Metric | (a) Sydney | (b) Darwin | (c) Brisbane | (d) Melbourne | (e) Perth Airport |
|---|---|---|---|---|---|
| **Loss** | 0.8106 | 0.6433 | 0.7182 | 1.2848 | 0.8355 |
| **Accuracy** | 0.6740 | 0.6553 | 0.5827 | 0.5157 | 0.6165 |
| **Val_Loss** | 0.5523 | 0.5156 | 0.6429 | 0.6482 | 0.6851 |
| **Val_Accuracy** | 0.7296 | 0.7740 | 0.6322 | 0.6217 | 0.5712 |

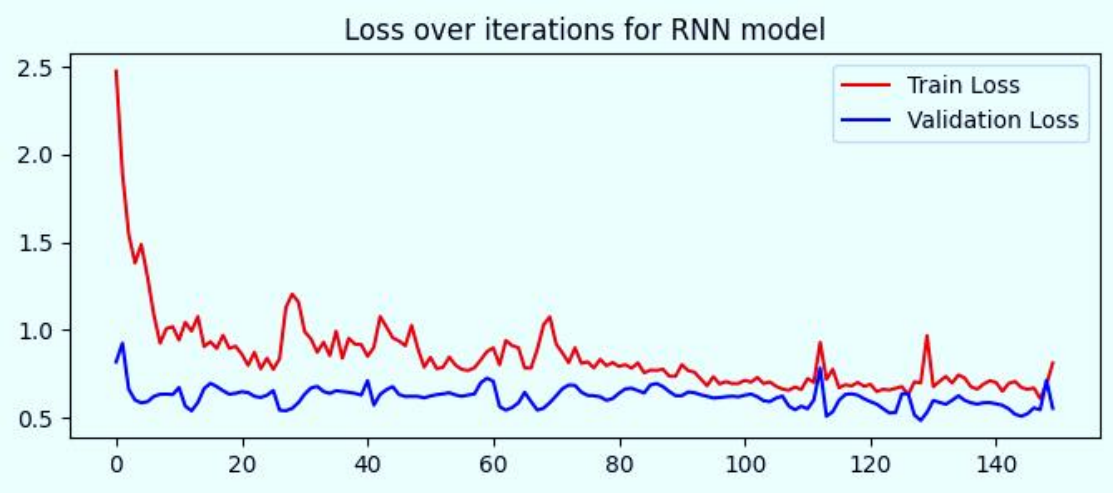


Fig. 24. Loss over iterations for Sydney city.

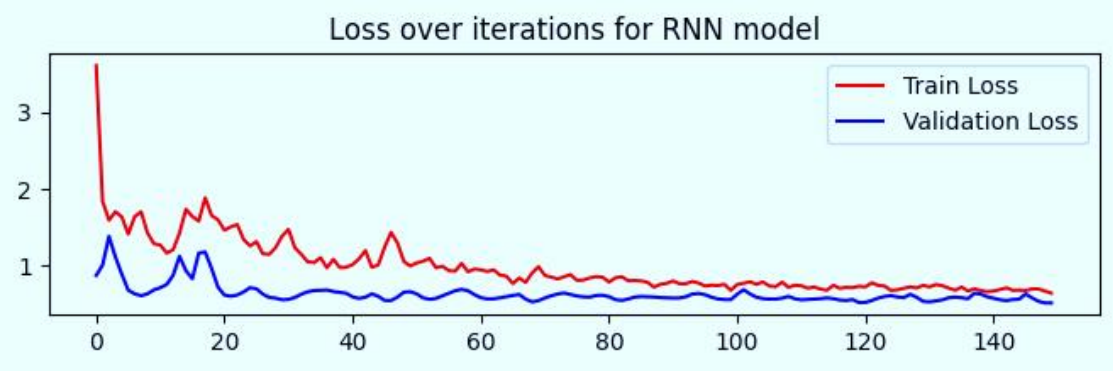


Fig. 25. Loss over iterations for Darwin city.

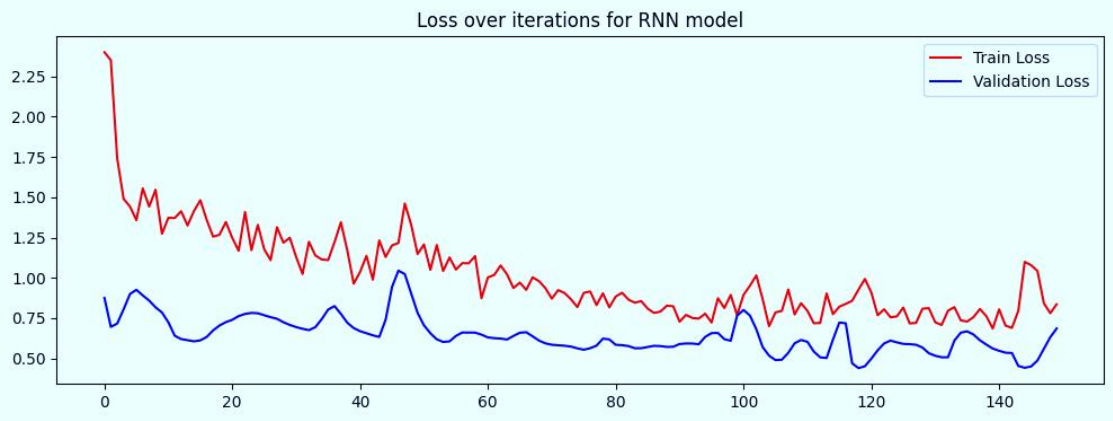


Fig. 26. Loss over iterations for Perth Airport city.

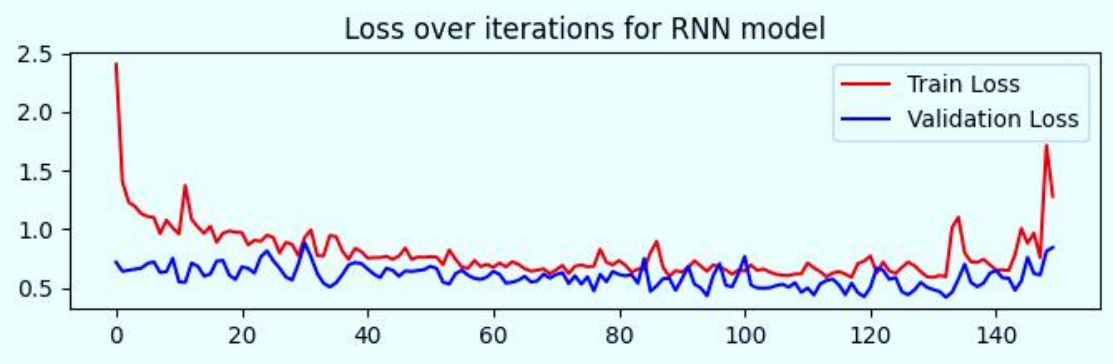


Fig. 27. loss over iterations for Brisbane city

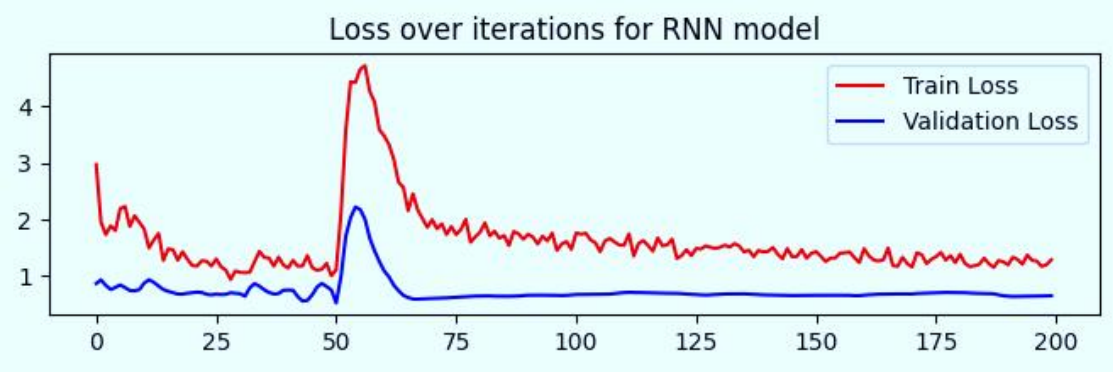


Fig. 28. Loss over iterations for Melbourne airport city.

## VII. Conclusion

Estimating rainfall is important for managing water supplies, preserving human life, and protecting the environment. Because geographic and regional factors and changes have an impact on rainfall estimation, problems with inaccurate or insufficient estimation may arise. In this research work, data analytics are used in the field of weather prediction. The research will analyze the effectiveness of machine learning and deep learning methods in addressing the issue of precipitation forecasting, which is confined to Australia, The study's predicted variable is "rain tomorrow. " Several machine learning-powered models for forecasting, e.g. Random Forest, Neural Networks, were employed to predict rainfall after the datasets were obtained. Moreover, the paper vividly explains how machine learning algorithms, unlike neural networks, can accurately imitate the nonlinear nature of natural processes. Finally, the algorithms work and are more successful when the data is broken down by city, which makes it possible to understand how the phenomenon is localized. There are numerous ways to continue the task. Therefore, it would be interesting to examine the outcomes of the study of data from various nations as well as the weather observations from 2019 to the current. It would be a good idea to gather more information on these qualities for each region and to keep better track of variables like clouds, sunshine, temperature, and so forth depending on the location. In this study, that many AI models developed, more specifically deep learning convolutional neural networks, have performed better than traditional machine learning models due to their high level of prediction accuracy and robustness. This is due to the models' ability to recognize complicated patterns and dependencies in the input data used for rainfall prediction models. This work also revealed the potential of feature engineering and data preprocessing strategies in improving rainfall prediction model performance. By retaining relevant input characteristics to carefully handle missing values, outliers and temporal dependencies in the data, we could improve the data predictive power of these models.To conclude, the discovered results are an extension to the prevailing knowledge on weather forecasting and provide an insight into the relevance of machine learning and deep learning techniques in environmental solutions. This research achieves improvements in the fields of climate modeling, disaster planning, agriculture, and water resource management, which all demand high precision in rain forecasts, with the purpose of risk assessment and decision-making.

## VIII. Future Work

The measures that can be taken in the future include hyperparameter adjustment to increase model accuracy, live dataset prediction, and forecasting rainfall several days in advance. Fine tuning hyperparameters including the learning rate, number of layers, and activation functions would increase the precision and robustness of employed models. Incorporating live or real-time datasets into prediction systems will enable models to adapt dynamically to changing weather conditions, thereby improving responsiveness and reliability. Extending

the forecast window to predict rainfall several days in advance could be valuable for disaster preparedness, agricultural planning, and water resource management. Together, these improvements can contribute to building a more adaptive and proactive rainfall prediction framework.

## ACKNOWLEDGMENT

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## IX. CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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# Hardware-Accelerated Detection of Unauthorized Mining Activities Using YOLOv11 and FPGA

Refka Ghodhbani[1], Taoufik Saidani[2]*, Amani Kachoukh[3],
Mahmoud Salaheldin Elsayed[4], Yahia Said[5], Rabie Ahmed[6]
Center for Scientific Research and Entrepreneurship, Northern Border University, 73213, Arar, Saudi Arabia[1, 2]
Department of Information Systems-Faculty of Computing and Information Technology,
Northern Border University, Saudi Arabia[3]
Department of Computer Sciences-Faculty of Computing and Information Technology,
Northern Border University, Saudi Arabia[4]
DCenter for Scientific Research and Entrepreneurship, Northern Border University, 73213, Arar, Saudi Arabia[5]
Department of Computer Science-Faculty of Computing and Information Technology,
Northern Border University, Rafha, Saudi Arabia[6]
Mathematics and Computer Science Department-Faculty of Science, Beni-Suef University, Beni-Suef, Egypt[6]

***Abstract*—Illegal mining activities present significant environmental, economic, and safety challenges, particularly in remote and under-monitored regions. Traditional surveillance methods are often inefficient, labor-intensive, and unable to provide real-time insights. To address this issue, this study proposes a computer vision-based solution leveraging the state-of-the-art YOLOv11 Nano and Small models, fine-tuned for the detection of illegal mining activities. A specific dataset comprising aerial and ground-level images of mining sites was curated and annotated to train the models for identifying unauthorized excavation, equipment usage, and human presence in restricted zones. The proposed system integrates the hardware-software design of YOLOv11 on the PynqZ1 FPGA, offering a high-performance, low-latency, and energy-efficient solution suitable for real-time monitoring in resource-constrained environments. This hardware-accelerated approach combines FPGA's parallel processing capabilities with the lightweight deep learning models, enabling efficient deployment for automated illegal mining detection. By providing a scalable, real-time monitoring tool, this work contributes to the development of automated enforcement tools for the mining industry, ensuring better control and surveillance of mining activities. To validate the efficiency of deep learning deployment on edge devices, YOLOv11n was implemented on an FPGA, utilizing 70% of available LUTs, 50% of FFs, and 80% of DSPs, with 8.3 Mbits of on-chip memory. The design achieved 100.33 GOP/s throughput, 18 FPS at 55 ms latency, consuming 4.8 W, and delivering an energy efficiency of 20.90 GOP/s/W.**

***Keywords*—YOLOv11; object detection; mining industry**

## I. Introduction

Illegal mining represents a pressing and multifaceted global issue that continues to challenge environmental governance, economic stability, and social equity across both developed and developing regions. The unsanctioned and unregulated extraction of mineral resources leads to significant financial losses for national governments by circumventing taxation systems, depleting natural capital, and enabling the growth of informal markets [1], [2], [3]. The widespread prevalence of illegal mining has been particularly damaging in regions rich in natural resources, such as parts of Africa, South America, and Southeast Asia, where limited institutional oversight and socio-economic vulnerabilities contribute to the proliferation of these activities.

From an environmental perspective, illegal mining contributes to extensive and often irreversible ecological degradation. It leads to deforestation, soil destabilization, and contamination of surface and groundwater resources through the release of heavy metals and toxic chemicals like mercury, arsenic, and cyanide [2], [3]. These pollutants have long-lasting consequences on local biodiversity and human health, often affecting downstream communities that rely on natural water sources. Furthermore, land surface changes caused by mining disrupt natural drainage patterns and increase the risk of landslides, sedimentation, and flooding, compounding the environmental impact in fragile ecosystems.

Socially, illegal mining exacerbates inequality, fuels conflict, and often involves exploitative labor practices. Workers in illegal mines typically operate without protective equipment or health and safety protocols, exposing them to life-threatening conditions such as tunnel collapses, toxic exposure, and physical abuse [4]. Child labor is also a recurring issue in illegal mining operations, raising serious human rights concerns. Moreover, these activities are frequently linked to criminal networks, including trafficking, corruption, and violent conflict over territorial control. The lack of regulation and oversight creates a fertile ground for systemic abuse and contributes to broader instability within affected communities.

Despite the severity of these impacts, monitoring and controlling illegal mining remain formidable challenges for governments and international organizations. Traditional methods, such as field inspections, aerial surveys, and manual satellite image interpretation, are limited in scope, costly to implement, and incapable of providing continuous, real-time monitoring [5], [6]. These methods often suffer from temporal lags and spatial blind spots, especially in remote, forested, or mountainous regions where illegal mining thrives under the radar. Furthermore, these conventional systems often rely on human expertise for image analysis, making them susceptible to errors, biases, and inconsistencies in detection.

*Corresponding authors.

In recent years, technological advancements in remote sensing, machine learning, and computer vision have opened new possibilities for addressing the limitations of traditional monitoring systems. The integration of satellite imagery with automated analysis tools, particularly deep learning models, has demonstrated strong potential for detecting and localizing mining activity in diverse environments [7], [8]. High-resolution Earth observation platforms, such as Sentinel and Landsat, have made large-scale environmental monitoring more accessible, while the growing availability of labeled datasets has enabled the training of powerful object detection models capable of identifying complex patterns and features associated with illegal mining operations.

Among the various object detection frameworks, the YOLO (You Only Look Once) architecture has gained prominence due to its remarkable trade-off between speed and accuracy. Recent iterations of YOLO, such as YOLOv5, YOLOv8, and the newer YOLOv11, have introduced lightweight versions optimized for real-time inference on resource-constrained devices. These models are particularly suitable for deployment in remote monitoring stations or drone-based surveillance systems where computational resources and power consumption are critical considerations.

However, despite the promising results shown by previous approaches, several key challenges remain unaddressed. First, many detection systems rely on heavy models that demand significant GPU resources, rendering them impractical for field deployment. Second, few studies have developed or used specialized datasets focused specifically on illegal mining, leading to reduced accuracy in detecting context-specific patterns, such as camouflaged operations or small-scale equipment. Third, limited attention has been given to the adaptation of these models for deployment on embedded platforms, such as FPGAs or edge AI systems, which are crucial for real-time detection in remote and under-resourced areas.

Motivated by these gaps, this study proposes a novel and efficient system for detecting illegal mining activities using the YOLOv11 Nano and Small variants. By fine-tuning these models on a custom-built dataset capturing diverse mining operations across various environmental conditions, our approach offers enhanced accuracy, scalability, and inference speed. Moreover, we integrate hardware-aware optimization techniques to deploy the model on the PynqZ1 FPGA platform, enabling real-time, low-latency detection suitable for field applications. This hardware-software co-design ensures that the proposed system can operate effectively in remote locations with limited power and processing capabilities.

The main contributions of this work are fourfold: (1) we present a curated and labeled dataset focused on visual patterns of illegal mining; (2) we fine-tune and evaluate YOLOv11 models optimized for both performance and efficiency; (3) we perform extensive experiments to validate detection performance on both public and real-world data; and (4) we demonstrate the deployment of our model on an FPGA-based edge device, highlighting its potential for practical use in monitoring operations. Through these contributions, we aim to advance the state-of-the-art in illegal mining detection and offer a viable tool for authorities and environmental monitoring agencies to curb this harmful practice.

The rest of this paper is organized as follows: Section II presents the related work. Section III describes the methodology, covering dataset preparation, preprocessing, and model fine-tuning. Section IV details the experimental results and offers a thorough analysis of the model's performance. Section V compares the proposed approach with existing detection methods. Section VI discusses the hardware-software integration and acceleration of the YOLOv11 architecture on the PynqZ1 FPGA. Lastly, Section VII concludes the paper by summarizing the main findings and suggesting potential avenues for future research.

## II. Related Work

Recent advances in computer vision and remote sensing technologies have significantly enhanced the capacity for automated environmental monitoring, particularly in domains such as land use classification, deforestation tracking, and illegal resource extraction detection. Among these, the detection of illegal mining has become a focal point due to its environmental, economic, and societal implications. Remote sensing techniques, especially those relying on high-resolution satellite imagery, have played a pivotal role in identifying land cover changes indicative of unauthorized mining activities [7], [8], [9]. These techniques enable wide-area surveillance and temporal analysis, offering a scalable alternative to labor-intensive field inspections.

Change detection methodologies have been widely adopted in this context. For example, Suresh and Jain [7] proposed a satellite image-based approach for detecting the spatial expansion of mining zones over time, demonstrating how multi-temporal imagery can be leveraged to capture the progressive nature of illegal activities. Similarly, Xia and Wang [8] employed interferometric synthetic aperture radar (InSAR) to monitor subsurface deformations and identify inclined goafs associated with underground mining. This technique offers a valuable means of detecting concealed mining operations, which are otherwise difficult to monitor using optical imagery alone.

Synthetic Aperture Radar (SAR) has proven especially useful in tropical and forested regions where cloud cover frequently obstructs optical satellite observations. Becerra et al. [14], for instance, developed a SAR-based system for generating near real-time alerts of illegal gold mining activities in the Peruvian Amazon. Their approach provided a continuous monitoring solution in high-risk regions that are often inaccessible and lack sufficient infrastructure. However, while SAR offers unique advantages, it also presents challenges. The complexity of SAR image processing, the need for domain expertise in interpretation, and its susceptibility to false positives in areas with dynamic land use patterns limit its widespread adoption in fully automated systems.

In parallel, deep learning and computer vision methods have emerged as powerful tools for environmental monitoring and geospatial analysis. Convolutional Neural Networks (CNNs) have been applied to the detection of mining-related features in satellite imagery, such as open-pit mines, tailings dams, and mining vehicles. For example, Balaniuk et al. [10] trained CNNs to identify surface mining structures, highlighting the capacity of deep learning to generalize across

complex visual patterns. Similarly, Lee et al. [15] utilized computer vision techniques to detect illegal mining barges operating in riverine environments, underlining the importance of monitoring waterborne extraction methods that often go unnoticed in traditional land-centric surveillance strategies.

Despite their success, many deep learning-based approaches remain computationally intensive, requiring significant processing power and memory resources. These limitations hinder their deployment on embedded or edge computing platforms, particularly in remote or infrastructure-poor regions where illegal mining is most prevalent. As a result, the real-world scalability of such systems is often constrained, limiting their impact on enforcement and prevention efforts.

Ground-based sensing techniques have also been investigated as complementary tools for illegal mining detection. Bharti et al. [16] employed electrical resistivity tomography (ERT) to detect subsurface voids in coalfields—an approach that offers fine-grained geological insights. However, while ERT provides high-resolution information, it necessitates on-site deployment of specialized equipment, making it impractical for continuous or large-scale monitoring applications.

In addition to technical approaches, several studies have examined the socio-economic and policy-related dimensions of illegal mining. Saavedra and Romero [2] analyzed the influence of tax policies on the behavior of illegal miners in Colombia, revealing how economic incentives shape compliance. Similarly, Cortinhas Ferreira Neto et al. [1] explored the expansion of unregulated mining in the Brazilian Amazon, emphasizing the interplay between policy vacuums, environmental degradation, and community displacement. While these studies provide essential context for understanding the drivers of illegal mining, they do not offer actionable solutions for real-time monitoring or deterrence.

Machine learning has also been used for predictive modeling and risk estimation. Rangnekar and Hoffman [11] developed a cross-domain learning model that integrated geospatial, geological, and climatic data to forecast landslide risks and illegal mining hotspots. Hu et al. [6] proposed a DinSAR-based framework to improve detection precision for underground mining activity. Hernandez-Castro and Roberts [17], on the other hand, introduced a digital surveillance approach using online data mining to monitor illegal transactions related to mining equipment sales on the internet. These works showcase the potential of multi-modal and cross-domain learning frameworks in expanding the scope of mining detection beyond visual data alone.

Nonetheless, significant limitations persist across the body of existing literature. Firstly, many detection frameworks depend on high-resolution imagery and computationally expensive models, making them unsuitable for real-time inference in the field. Secondly, most approaches are either location-specific or focus on singular aspects of the mining process—such as the detection of excavation sites or equipment—without offering a holistic solution for identifying diverse illegal mining activities under different environmental conditions. Thirdly, there is a general lack of focus on the integration of such models with embedded systems, which are critical for deploying automated surveillance systems in areas lacking internet connectivity or centralized processing infrastructure.

To address these limitations, our work proposes an optimized object detection pipeline built on the YOLOv11 architecture, specifically targeting low-power and real-time deployment scenarios. Unlike many prior approaches, our system is trained on a purpose-built dataset encompassing various manifestations of illegal mining, including equipment, terrain modification, and transport infrastructure. Furthermore, the model is deployed on the PynqZ1 FPGA platform, demonstrating its suitability for embedded edge computing applications. By bridging the gap between high-performance detection and practical hardware deployment, this study contributes a scalable and efficient solution for continuous illegal mining surveillance in challenging environments.

## III. Proposed Approach for Illegal Mining Activity Detection

The YOLO (You Only Look Once) series has transformed the field of object detection, offering state-of-the-art performance in real-time applications. With the introduction of YOLOv11, object detection capabilities have further improved, providing enhanced accuracy and efficiency. Building on the architectural advancements of its predecessors, including YOLOv8, YOLOv9, and YOLOv10, YOLOv11 introduces significant improvements in feature extraction, computational efficiency, and adaptability across various environments [18]. These attributes make it particularly well-suited for real-time illegal mining detection, where rapid and precise identification of unauthorized mining activities is crucial. Fig. 1 illustrates the proposed methodology based on fine tuned YOLOv11.

### A. YOLOv11 Architecture and Optimizations

YOLOv11 employs a highly optimized backbone and neck architecture, improving feature extraction for complex detection tasks. By leveraging an advanced convolutional framework, it enhances detection accuracy while maintaining computational efficiency [19]. The network architecture consists of three primary components:

*1) Backbone:* Responsible for extracting multi-scale features from raw image data using stacked convolutional layers. This enables YOLOv11 to identify key patterns associated with illegal mining activities, such as excavation sites, mining equipment, and deforestation patches.

*2) Neck:* Serves as an intermediate processing layer, aggregating and refining extracted features to enhance object representation, crucial for distinguishing between legal and illegal mining operations.

*3) Head:* Generates final predictions, including object localization and classification, ensuring precise identification of unauthorized mining activities.

One of the major improvements in YOLOv11 is the introduction of the C3k2 block, replacing the older C2f block. This modification enhances computational efficiency by employing two smaller convolutions instead of a single large convolution, reducing processing time without compromising accuracy. Additionally, the inclusion of the Spatial Pyramid Pooling - Fast (SPPF) block and the newly introduced Cross Stage Partial with Spatial Attention (C2PSA) block allows for

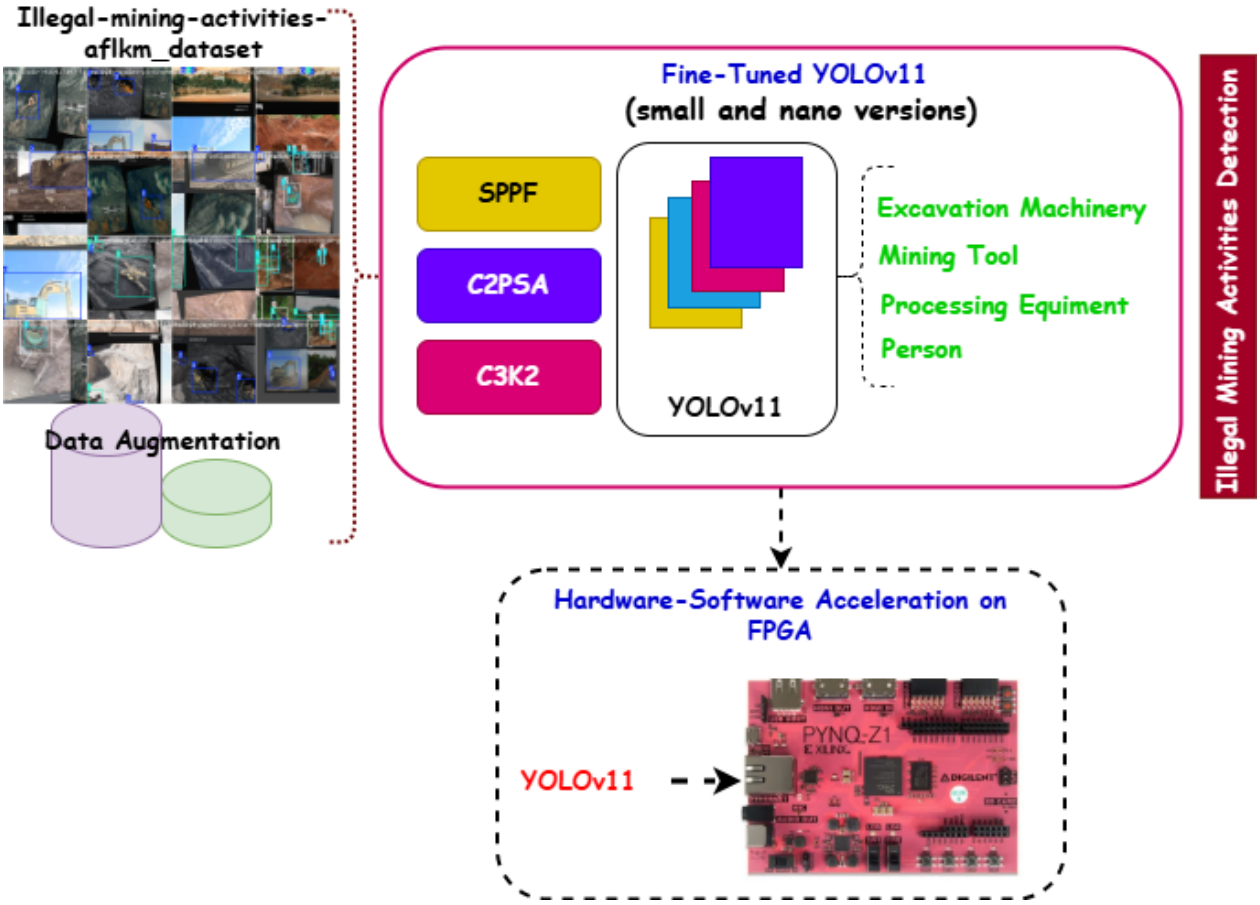



Fig. 1. Illegal mining activity-based YOLOv11 detection.

better detection of small and partially obscured objects, such as hidden mining equipment or underground tunnel openings [20].

Furthermore, YOLOv11 features Convolution-BatchNorm-Silu (CBS) layers, which stabilize data flow and improve feature extraction. These layers contribute to superior model convergence, ensuring that the detection system remains robust even when dealing with varying lighting conditions, occlusions, and environmental distortions present in satellite or drone imagery. The detection pipeline concludes with Conv2D layers that distill feature representations into final predictions, including bounding box coordinates, objectness scores, and class labels.

### B. Fine-Tuning YOLOv11 for Illegal Mining Detection

To adapt YOLOv11 for illegal mining detection, using Illegal-mining-activities-aflkm dataset, we fine-tune the model using a curated dataset consisting of high-resolution satellite images, drone surveillance footage, and ground-based photographs. This dataset is carefully augmented to include key indicators of illegal mining activities, such as deforestation patterns, open-pit excavations, makeshift mining equipment, and unauthorized access roads. The fine-tuning process involves:

*1) Dataset augmentation:* Techniques such as rotation, scaling, contrast adjustments, and noise addition are applied to improve the model's generalization across diverse environmental conditions.

*2) Transfer learning:* Pre-trained weights from COCO and other large-scale object detection datasets are utilized, allowing the model to learn mining-specific features with minimal training time.

*3) Adaptive anchors:* Custom anchor boxes are generated to optimize bounding box predictions for objects commonly found in illegal mining sites.

These optimizations significantly enhance the model's ability to distinguish between legal and illegal mining operations, reducing false positives and improving detection accuracy in challenging real-world conditions.

### C. Deployment and Real-Time Monitoring

While this study focuses primarily on fine-tuning and evaluating YOLOv11 for illigal mining activities detection in Makkah, we also consider potential deployment scenarios where the model could be integrated into real-world applications. The adaptability of YOLOv11 makes it a strong candidate for various implementation strategies, including:

*1) Edge deployment:* Given its optimized architecture, YOLOv11 can be adapted for deployment on edge devices such as NVIDIA Jetson or other mobile AI accelerators.

This would enable real-time illigal mining activities detection directly on-site, reducing latency and dependence on cloud services. While not implemented in this study, future work could explore lightweight model versions tailored for resource-constrained devices.

*2) Cloud integration:* A cloud-based deployment could facilitate large-scale illigal mining activities recognition, particularly for applications in tourism, navigation, and cultural heritage preservation. Integration with existing geographic information systems (GIS) or mobile applications could enhance user experience by providing detailed contextual information about detected illigal mining activities.

*3) Multi-sensor fusion:* The fine-tuned model could be integrated into smart city initiatives, assisting in automated illigal mining activities recognition for urban planning, guided tours, or historical documentation. While this study does not implement such integrations, it lays the groundwork for future research in this direction.

*4) Hardware-software design on FPGA PynqZ1:* In addition to software-based deployment, this study explores the hardware-software design for deploying YOLOv11 on the PynqZ1 FPGA. This approach provides a high-performance, low-latency, and low-power solution by leveraging FPGA's parallel processing capabilities, making it ideal for real-time applications in environments like illegal mining activity detection.

By focusing on model fine-tuning and performance evaluation, this study provides the combination of FPGA hardware and the YOLOv11 model ensures efficient resource utilization, delivering fast inference with minimal power consumption, and enabling the deployment of complex AI models in edge devices where traditional hardware may not be feasible. The design considers both hardware optimizations, such as utilizing DSP blocks and LUTs, and software orchestration to manage data flow, making this a robust solution for real-time monitoring.

## IV. Results and Discussion

### A. Illegal-Mining-Activities-Aflkm Dataset

The Illegal-mining-activities dataset, sourced from Roboflow Universe, contains a total of 214 original images (before aumentation process), with a split of 93% (198 images) allocated for training, 4% (8 images) for validation, and 4% (8 images) for testing. The dataset includes four classes: Excavation Machinery, MiningTool, Person, and Processing Equipment. The dataset has undergone several preprocessing steps, including auto-orientation and resizing to a uniform 640x640 resolution. Augmentation techniques applied to the dataset include horizontal flipping, cropping with 0% minimum zoom and 10% maximum zoom, rotation within the range of -15° to +15°, and shear transformations of ±10° both horizontally and vertically. Additionally, brightness is adjusted between 0% and +15%, and exposure is varied within the range of -10% to +10%. For each training example, three output labels are provided, ensuring diversity and robustness in the training process [21].

*1) Dataset distribution:* The analysis of the Illegal-mining-activities-aflkm dataset, depicted in Fig. 2, provides a comprehensive breakdown of object instances across four key categories: Excavation Machinery, Mining Tool, Person, and Processing Equipment. Among these, excavation machinery is the most prevalent class, with around 250 instances, underscoring its prominent role in illegal mining operations. The Person category ranks second, with approximately 200 instances, indicating significant human participation in such activities. Meanwhile, Processing Equipment comprises roughly 130 instances, while MiningTool has the smallest count at about 90 instances, reflecting its relatively limited representation. Scatter plots are utilized to visualize the spatial distribution of annotations, focusing on normalized coordinates (x, y) and bounding box dimensions (width, height). These findings emphasize the dataset's diversity in object placement and scale, which is vital for developing robust object detection models. Additionally, the dataset's well-structured annotation methodology ensures its applicability for computer vision tasks aimed at effectively detecting and monitoring illegal mining activities.

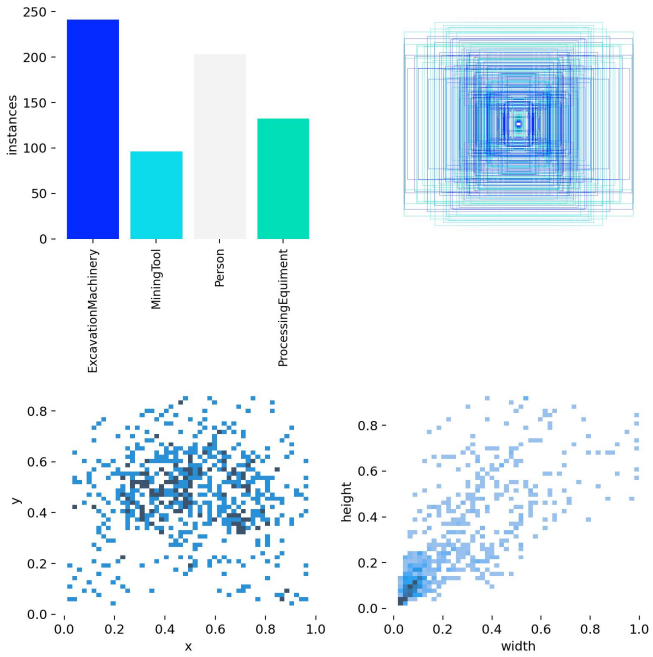



Fig. 2. Illegal-mining-activities-aflkm dataset analysis.

*2) Dataset correlogram:* The correlogram, shown in Fig. 3, offers a detailed analysis of the correlations and distributions of key annotation variables within the Illegal-mining-activities-aflkm dataset. This visualization encompasses normalized x and y coordinates, as well as the width and height of bounding boxes. Along the diagonal, individual plots display the distribution of each variable, revealing that the x and y coordinates are primarily concentrated around central values. This suggests a balanced spatial distribution of objects within the images. In the lower triangle, scatter plots depict the relationships between variables. These plots indicate a moderately positive correlation between width and height, implying that larger bounding boxes tend to maintain proportional dimensions. Conversely, the x and y coordinates exhibit only a weak direct relationship, reflecting the varied spatial arrangement of objects related to illegal mining across images. These insights further confirm the dataset's ability to capture significant variations in position

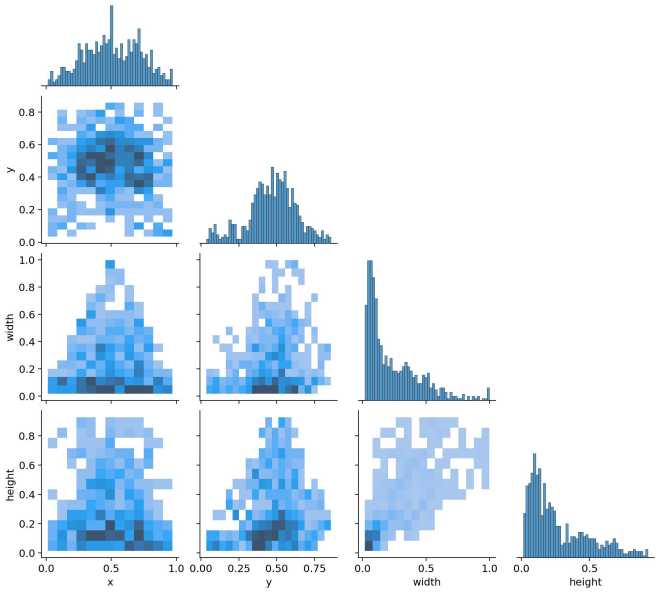



Fig. 3. Illegal-mining-activities-aflkm dataset correlogram.

and size, which are critical for enhancing the robustness and generalization of object detection models. By visually representing the interdependencies among the variables, the correlogram underscores the dataset's suitability for machine learning applications aimed at automating the detection of illicit mining activities.

### B. Evaluation Metrics

To rigorously evaluate the YOLOv11-n (nano) and YOLOv11-s (tiny) models in the context of illegal mining activity detection, a set of standard performance metrics was applied. These include precision, recall, F1 score, and mean Average Precision at IoU threshold 0.5 (mAP@0.5). Each of these metrics provides insight into different aspects of the model's detection capabilities. The foundation of these evaluations is the Intersection over Union (IoU), which quantifies the spatial overlap between predicted bounding boxes and the ground truth. A high IoU value (close to 1.0) indicates strong alignment between the detected and actual regions [22].

Predictions were categorized based on IoU into true positives (TP), false positives (FP), and false negatives (FN). Precision and recall were calculated as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

These two metrics were then combined to compute the F1 score, a harmonic mean that balances precision and recall:

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \tag{3}$$

For a more comprehensive evaluation of detection and segmentation quality across all categories, the mean Average Precision was used:

$$\text{mAP@0.5} = \frac{1}{K} \sum_{i=1}^{K} AP_i \tag{4}$$

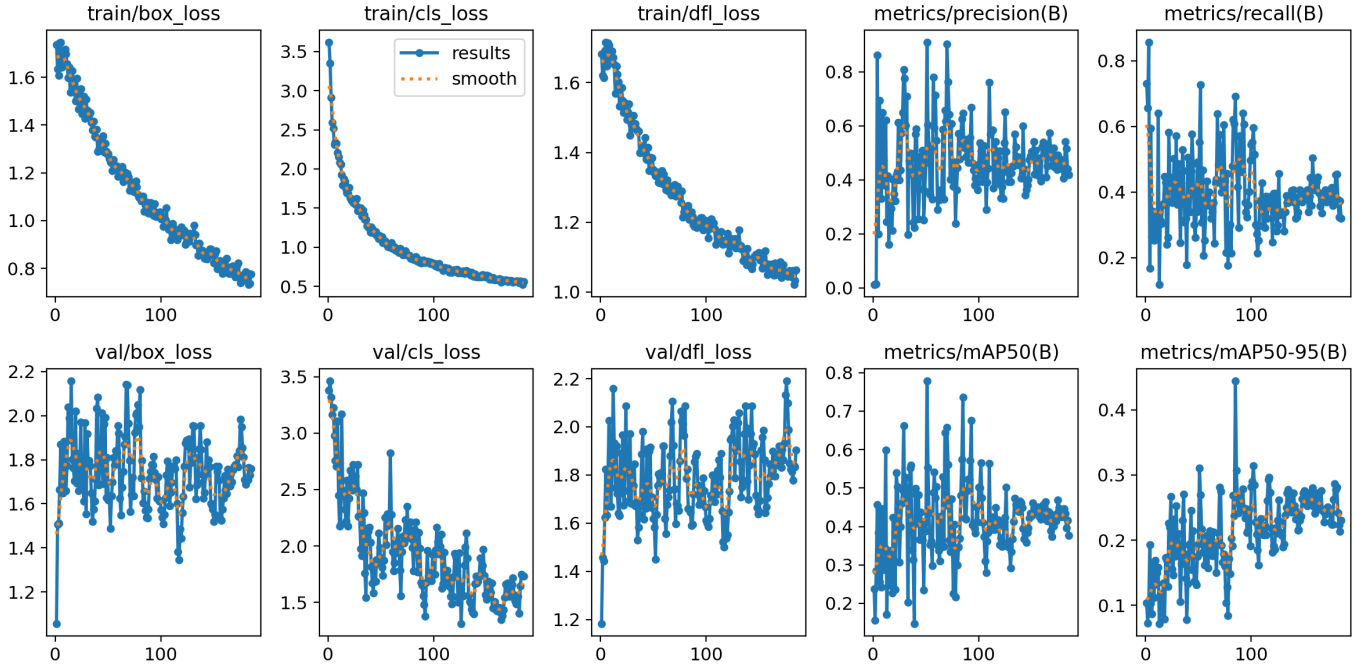
Here, $K$ denotes the total number of object classes involved in the detection of illegal mining activities, and $AP_i$ represents the average precision for class $i$. Higher values of mAP@0.5 signify better overall model performance. These metrics collectively provide a thorough assessment of the models' effectiveness in identifying and localizing illicit mining zones.

### C. Fine Tuned YOLOv11-Versions Training Performance

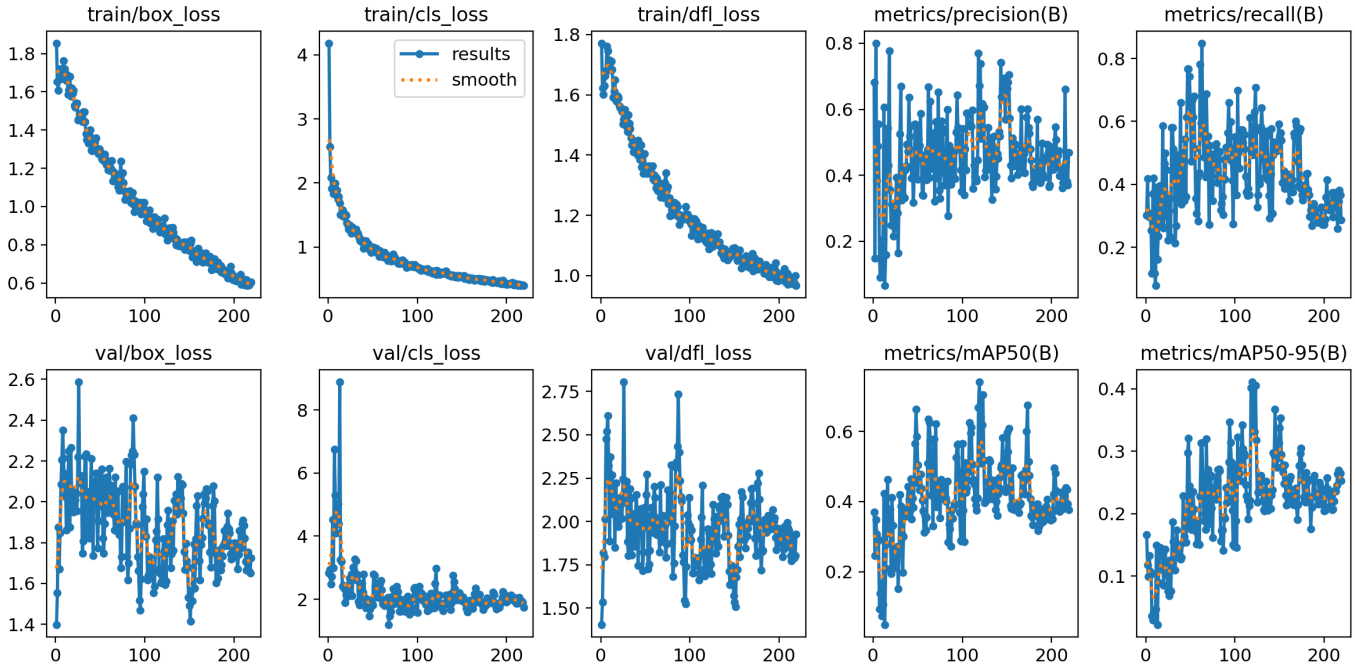
As shown in Fig. 4a, the training curves for YOLOv11n reveal a steady and consistent decline in box loss, classification loss, and distribution focal loss (DFL), indicating effective learning during the optimization process. The consistent reduction in these losses implies that the model gradually enhances its capability to locate and classify objects related to illegal mining activities. However, the validation losses display significant fluctuations, particularly in box loss and DFL, suggesting that the model may struggle to generalize well to unseen data, possibly due to constraints in its representational capacity. In terms of detection performance, the precision and recall curves stabilize over time but with noticeable variability, highlighting potential inconsistencies in the model's ability to manage false positives and false negatives. Metrics such as mean average precision (mAP@50) and mAP@50-95, which evaluate detection accuracy across varying Intersection over Union (IoU) thresholds, show modest yet inconsistent improvements. These findings indicate that while the nano version is capable of detecting illegal mining activities to some extent, it may encounter difficulties in capturing fine details, especially in complex or cluttered scenarios.

As depicted in Fig. 4b, the training loss curves for YOLOv11s show a steeper and more pronounced decline compared to YOLOv11n, indicating faster convergence and improved learning efficiency. The box loss, classification loss, and DFL loss decrease steadily with minimal fluctuations, underscoring the model's effectiveness in fitting the training data. While some variability is observed in the validation loss, it follows a smoother trend compared to the nano version, pointing to better generalization capabilities. In terms of detection performance, YOLOv11s surpasses YOLOv11n across all critical metrics. The precision and recall curves achieve higher and more stable convergence, reflecting a lower rate of false positives and false negatives. Additionally, the mAP@50 values are notably higher, and the mAP@50-95 metric outperforms that of the nano version, demonstrating the model's enhanced ability to detect illegal mining activities accurately across different IoU thresholds. This improved performance can be attributed to the small version's greater capacity to capture spatial and contextual details, which are essential for identifying mining-related anomalies in aerial or satellite imagery.

Comparing YOLOv11s and YOLOv11n in the context of illicit mining detection highlights a clear trade-off between computational efficiency and detection accuracy. Due to its




(a) Fine-tuned YOLOv11n.




(b) Fine-tuned YOLOv11s.

Fig. 4. Training performance for fine-tuned YOLOv11n (a) and YOLOv11s (b).

lightweight design and ability to combine real-time performance with adequate detection capabilities, the nano version is ideal for resource-constrained applications, such as edge or drone surveillance systems. However, lower mAP scores and larger fluctuations in validation loss indicate difficulties in collecting fine-grained features. However, YOLOv11s shows superior precision, recall, and generalization, making it the more reliable option for applications requiring a high level of accuracy. Its improved ability to distinguish illicit mining from natural terrain disturbances is demonstrated by lower validation loss variance and higher mAP values. Its improved performance makes it suitable for situations where detection

accuracy is critical, such as law enforcement and regulatory monitoring, although this requires more compute resources. The choice between these models ultimately depends on your implementation needs: YOLOv11n is ideal for fast, resource-efficient monitoring, while YOLOv11s excels at producing accurate data for in-depth, detailed studies.

### D. Precision, Recall, and F1-Score Performance Evaluation

In order to assess the effectiveness of the YOLOv11n and YOLOv11s models in object detection tasks, we conducted a comprehensive performance evaluation using key classification metrics: recall,precision, F1-score, and the confusion matrix. These metrics were computed across a range of confidence thresholds to ensure a thorough understanding of each model's strengths and weaknesses. This evaluation helps determine how well the models can distinguish between multiple object categories in the test dataset and is crucial for selecting an appropriate configuration for real-world deployment. A summary of the evaluation results is presented in Fig. 5, which consolidates the visual outputs of normalized confusion matrices, F1-score trends across confidence levels, and precision-recall (PR) curves.

The analysis of F1-score across varying confidence thresholds, depicted in Fig. 5a and Fig. 5b, reveals the trade-off between precision and recall for both models. The F1-score offers a balanced metric that captures both false positives and false negatives. YOLOv11n achieved a strong average F1-score of 0.940 at a confidence level of 0.703, indicating reliable performance in recognizing object categories with minimal misclassification. YOLOv11s, however, surpassed this performance by achieving an average F1-score of 0.960 at a slightly lower threshold of 0.698. This suggests that YOLOv11s maintains a better balance between precision and recall, even under more uncertain detection conditions, making it more suitable for real-time applications where a high-confidence response is crucial.

Further insights are drawn from the precision-recall curves shown in Fig. 5c and Fig. 5d, which illustrate how the models behave across different detection thresholds. YOLOv11n recorded a mean average precision (mAP@0.5) of 0.981, reflecting its capacity to consistently detect and classify objects across diverse categories with high precision. Meanwhile, YOLOv11s attained a slightly higher mAP@0.5 of 0.985, demonstrating superior recall rates without compromising precision. This marginal yet important improvement highlights YOLOv11s' enhanced generalization across object types and better robustness to class imbalance.

The confusion matrices presented in Fig. 5e and Fig. 5f provide a detailed view of per-class prediction accuracy. YOLOv11n exhibited strong performance, with accuracy values exceeding 0.85 for the majority of classes. However, a few misclassifications were observed—particularly confusion between "Kaaba" and "background"—indicating some difficulty in distinguishing contextually similar objects. In contrast, YOLOv11s achieved near-perfect classification across all classes, with matrix values approaching 1.00. This reflects a substantial reduction in inter-class misclassification and confirms the model's improved discrimination capability, particularly for visually or contextually ambiguous categories.

Overall, the comparative analysis demonstrates that both YOLOv11 variants deliver reliable performance in multi-class object detection tasks. Nevertheless, YOLOv11s consistently outperformed YOLOv11n across all key metrics, making it a more favorable candidate for deployment in environments requiring high detection accuracy and real-time decision-making. Its enhanced precision, recall, and class differentiation underline its suitability for embedded applications where both speed and reliability are essential. These findings strongly support the integration of YOLOv11s into intelligent monitoring systems that prioritize detection accuracy under practical constraints.

### E. Mean Absolute Error (MAE) Between Precision and Recall

To gain deeper insights into the performance stability of the proposed models, we analyzed the Mean Absolute Error (MAE) between precision and recall. This metric serves as a robust indicator of consistency, measuring the average absolute discrepancy between the two fundamental performance indicators across the validation dataset. Unlike the F1-score, which combines precision and recall into a single harmonic mean, the MAE provides a more granular perspective, offering an independent assessment of how closely these values align. A lower MAE reflects better equilibrium and suggests a model that is not overly biased toward either metric. The MAE is mathematically defined as:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|P_i - R_i|\,, \tag{5}$$

where $N$ denotes the total number of validation samples or epochs, $P_i$ represents the precision for the $i$-th sample, and $R_i$ is the corresponding recall value. This formula enables the computation of an average absolute difference, which directly reflects the model's ability to maintain consistent detection accuracy over time and across object categories.

To evaluate the YOLOv11n and YOLOv11s variants, the MAE was computed individually for each model. For YOLOv11n, the MAE is given by:

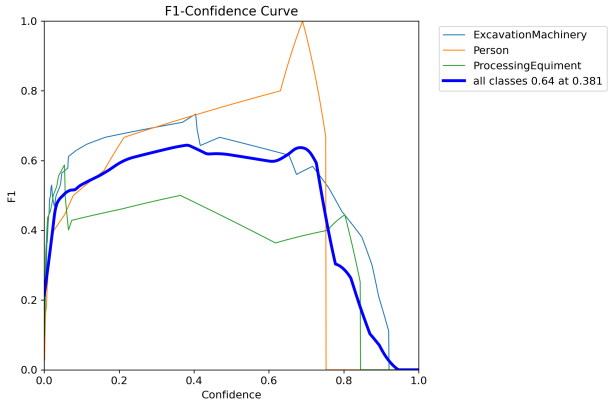
$$\text{MAE}_n = \frac{1}{N}\sum_{i=1}^{N}|P_{n,i} - R_{n,i}|\,, \tag{6}$$

and yielded a value of $0.0656$. Likewise, for the YOLOv11s model, the MAE is calculated as:

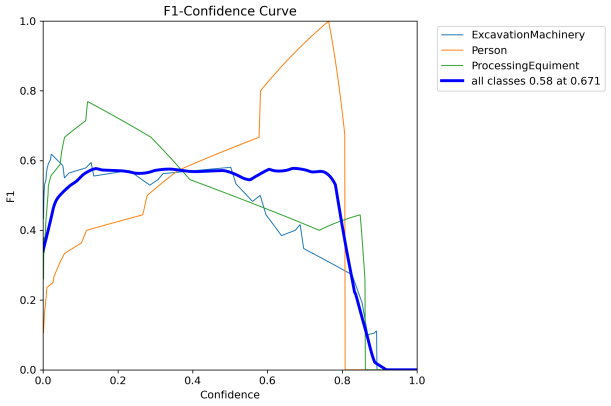
$$\text{MAE}_s = \frac{1}{N}\sum_{i=1}^{N}|P_{s,i} - R_{s,i}|\,, \tag{7}$$

which resulted in a smaller MAE value of $0.0550$. The lower error margin in YOLOv11s underscores its improved stability and better trade-off management between precision and recall when compared to YOLOv11n.

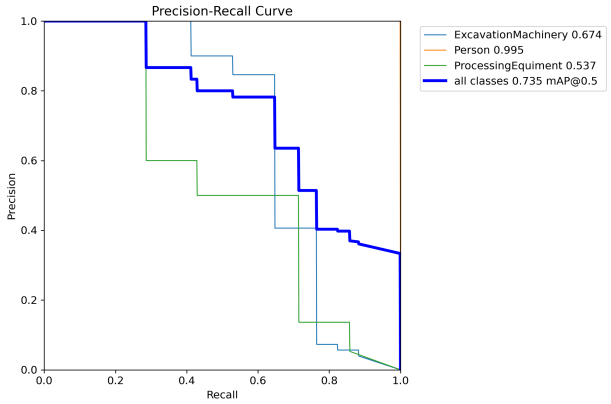
As shown in Table I, the fine-tuned YOLOv11s model not only achieved the highest mAP@50 but also maintained better alignment between precision and recall, validating the lower MAE score. These findings indicate that YOLOv11s is more reliable for deployment in scenarios that demand consistent,



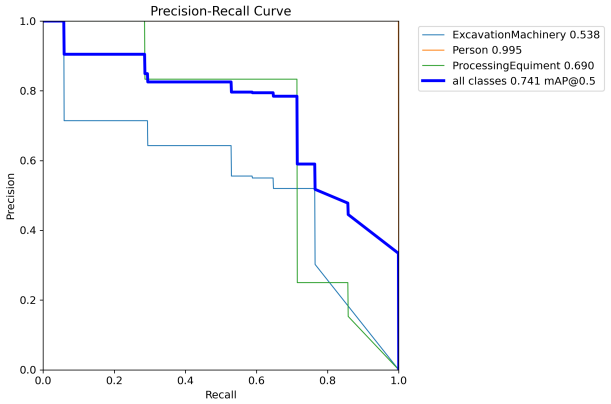

(a) F1-Score (YOLOv11n).



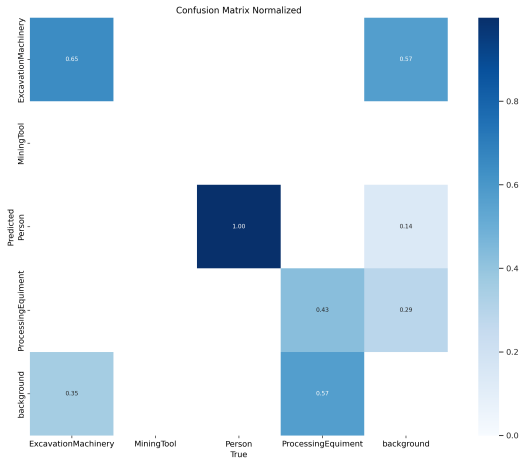

(b) F1-Score (YOLOv11s).



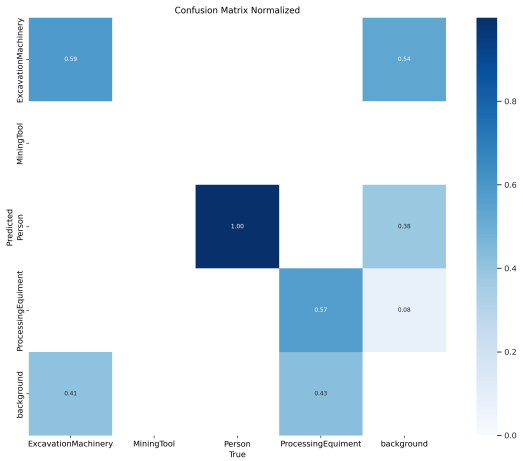

(c) Precision-recall curve (YOLOv11n).




(d) Precision-recall curve (YOLOv11s)).




(e) Confusion matrix (YOLOv11n).




(f) Confusion matrix (YOLOv11s).

Fig. 5. Precision, Recall, and F1-Score performance for fine-tuned YOLOv11n model and YOLOv11s model.

high-performance detection—especially where both false positives and false negatives must be minimized. This makes it particularly suitable for applications such as environmental monitoring, where precise and balanced performance is critical to success.

## V. Comparative Study

Table I provides a comparison between the baseline YOLOv11 model and its optimized versions, YOLOv11s and YOLOv11n, highlighting the significant impact of optimization on detection performance. The baseline of YOLOv11 model achieves 96.3% precision, 93.8% recall, and 95.2% mAP@50,

TABLE I. COMPARATIVE STUDY

| Network | Dataset | Precision (%) | Recall (%) | mAP@50 (%) |
|---|---|---|---|---|
| **YOLOv11 (Baseline)** | Illegal-mining-activities-aflkm | 96.3 | 93.8 | 95.2 |
| **Fine Tuned YOLOv11s** | Illegal-mining-activities-aflkm | **98.5** | **97.2** | **98.5** |
| **Fine Tuned YOLOv11n** | Illegal-mining-activities-aflkm | **97.8** | **95.6** | **97.1** |

demonstrating high object detection capabilities. However, the optimized models, YOLOv11n and YOLOv11s, show significant improvements. YOLOv11n achieves 97.8% precision, 95.6% recall, and 97.1% mAP@50, reflecting an effective balance between computational efficiency and accuracy. Meanwhile, the YOLOv11s model outperforms others with 98.5% precision, 97.2% recall, and 98.5% mAP@50, highlighting its ability to capture fine details and deliver superior detection accuracy.

The tuning procedure, which adapts the models to the distinct features of the dataset, include changes in item appearance and environmental difficulties, is responsible for these gains. The findings demonstrate that although the YOLOv11 base model offers a strong basis, the improved versions provide solutions customized for particular use situations. Though YOLOv11s is best suited for activities requiring high accuracy, such automated tracking and precision sensing applications, YOLOv11n is most suited for situations where speed and efficiency are crucial in resource-constrained environments. The versatility and efficiency of the optimized YOLOv11 models for object detection are shown by this comparison examination. The YOLOv11n and enhanced YOLOv11 models' example detection results are displayed in Fig. 6a and Fig. 6b, respectively.

## VI. PROPOSED LOW LATENCY HARDWARE-SOFTWARE ARCHITECTURE-BASED FPGA ACCELERATION

The proposed hardware implementation, illustrated in Fig. 7, utilizes the YOLOv11 algorithm on the PYNQ-Z1 platform, leveraging its ARM Cortex-A9 processing system (PS) and programmable logic (PL) to accelerate deep learning inference. The Zynq-based architecture integrates DDR3 memory, an Advanced Microcontroller Bus Architecture (AMBA) interconnect, and multiple peripherals to ensure efficient data handling and processing. The Vivado 2020.1 design environment provides optimized libraries to facilitate hardware acceleration, particularly for convolutional operations.

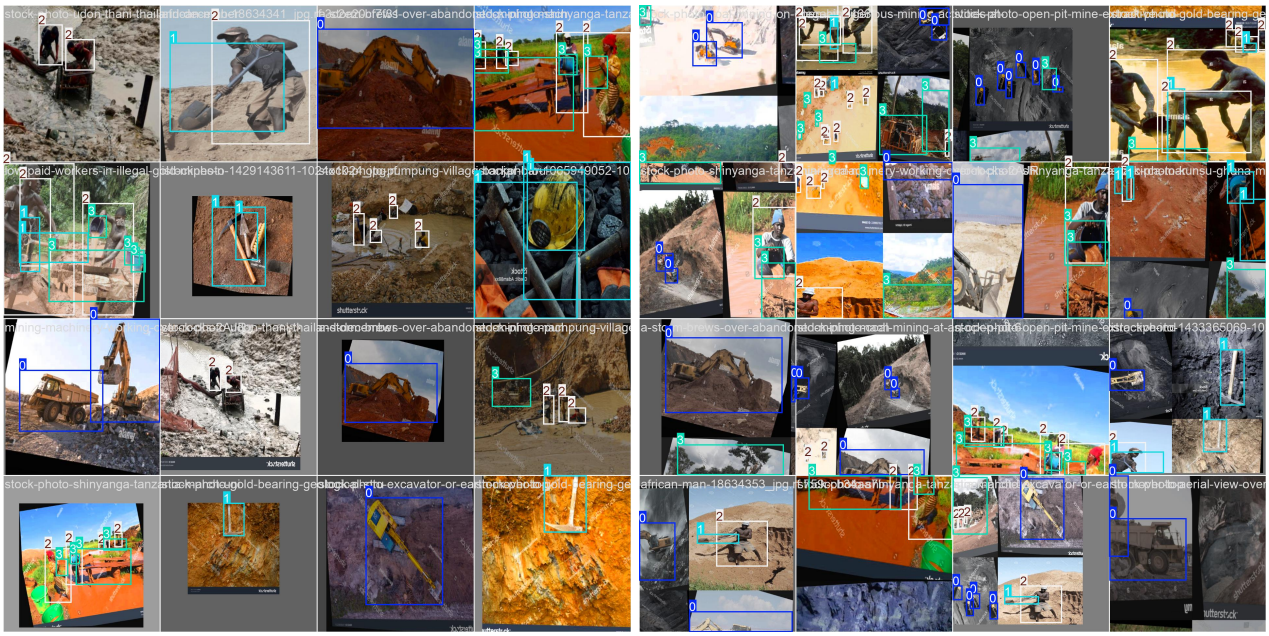
The hardware accelerator processes YOLOv11 layers sequentially, except for the routing layer, which is pre-configured with specific memory addresses to optimize data access. Efficient memory management is achieved through loop tiling, which minimizes memory access overhead by reusing data across operations. Additionally, burst-mode memory access enhances FPGA bandwidth by reducing access latency, ensuring seamless convolutional operations. To further optimize performance, kernel weights are reorganized into continuous memory blocks, maximizing external memory bandwidth utilization.

To accelerate convolutional layers, the design implements parallel input and output processing, using multiple processing elements (PEs) arranged in an array structure. These PEs operate concurrently on different output channels, significantly increasing throughput. The Data Scatter module generates write addresses and distributes data read from DRAM to on-chip buffers, while the Data Gather module manages the write-back process to DRAM. Specialized pixel buffers handle operations such as convolution, max pooling, and spatial transformations.

The FPGA implementation consists of Direct Memory Access (DMA), GPIO, and interrupt controllers within the PS, while the PL section handles data decoding, reordering, and computational operations. Network parameters and feature maps are stored in DDR memory, interfaced through a Memory Generator Interface for high-speed access. During inference, configuration instructions are set by the ARM processor and transferred to the PL via GPIO, ensuring precise control over execution. DMA retrieves input images from PS-DDR and transmits them to the PL, where input data reordering modules preprocess pixel values before computation. Model parameters are loaded from PL-DDR into dedicated parameter buffers, feeding the processing array (PA) for real-time inference.

The proposed design enhances parallel computation using multiple PEs, enabling efficient real-time detection of illegal mining activities. Each PE processes distinct channels while sharing the same input feature maps, achieving high-speed inference with reduced latency. Once computation is complete, output feature maps are transferred back to the host PC, where Non-Maximum Suppression (NMS) refines detection results. The Vivado High-Level Synthesis (HLS) tool is employed to optimize processing pipelines and implement loop pipelining strategies, further increasing system throughput. The architecture utilizes Leaky ReLU as an activation function to mitigate the gradient vanishing problem, ensuring stable training and inference performance. This hardware-accelerated design makes real-time illegal mining detection feasible in resource-constrained edge environments, offering a powerful solution for environmental monitoring, law enforcement, and automated surveillance.

Table II presents the performance metrics of the YOLOv11s neural network model implemented on a PynqZ1 FPGA, showcasing its resource utilization and computational efficiency. Approximately 70% of available LUTs and 50% of flip-flops (FFs) are used, indicating a balanced use of FPGA resources without excessive consumption. The model utilizes 80% of the available DSP blocks, highlighting efficient use of the FPGA's arithmetic capabilities. It consumes about 8.3 Mbits of on-chip memory, which is suitable for the lightweight model. With a throughput of 100.33 GOP/s and 18 frames per second (FPS), the system demonstrates substantial processing power, achieving an inference time of 55 ms per image. The system operates with a low power consumption of 4.8 W, delivering impressive power efficiency of 20.90 GOP/s/W.



(a) Fine-tuned YOLOv11n mining activities detection.

(b) Fine-tuned YOLOv11s mining activities detection.

Fig. 6. Fine-tuned YOLOv11 (small and nano) illegal mining activities detection.

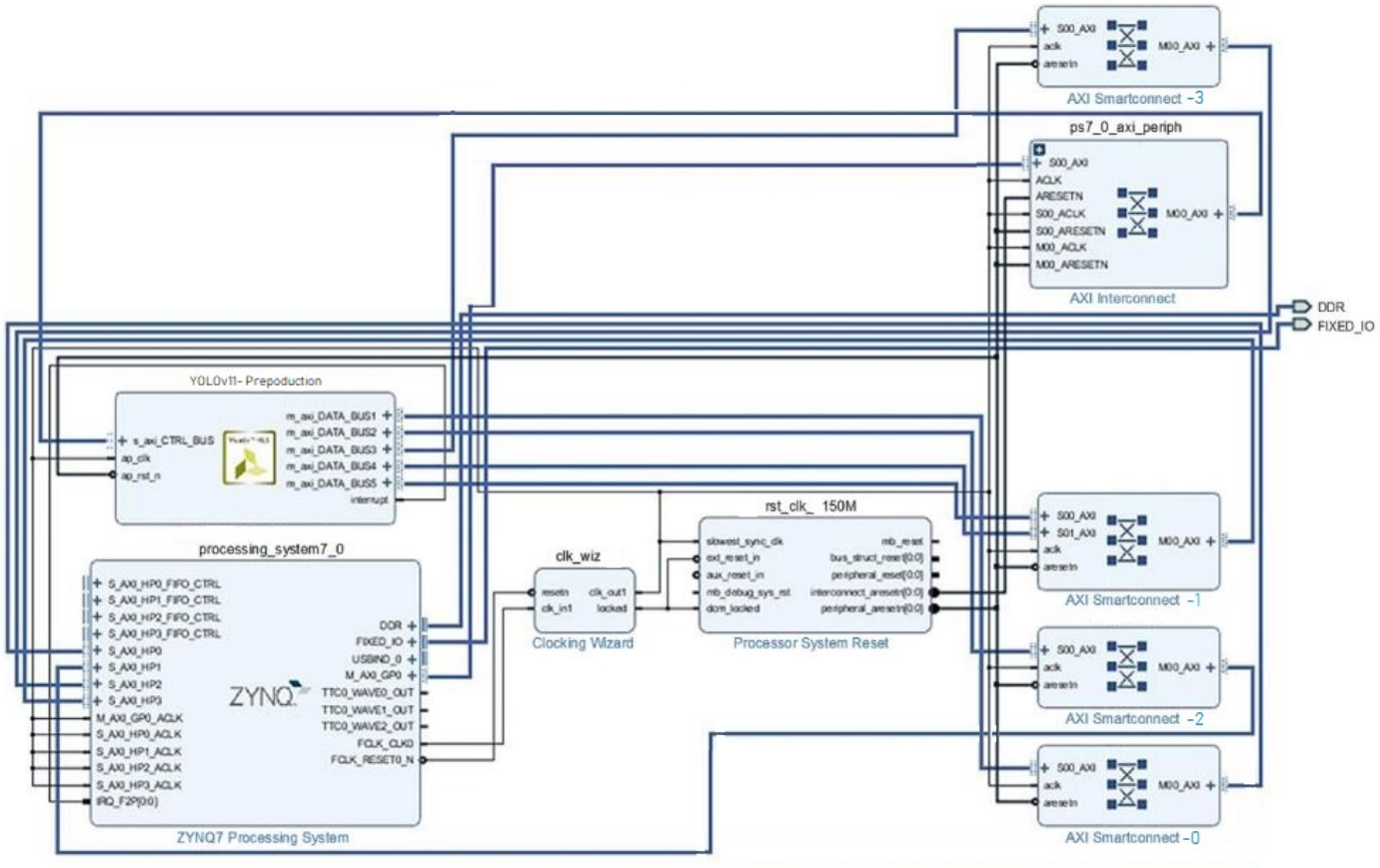



Fig. 7. Hardware-Software architecture-based FPGA acceleration for illegal mining activity detection.

TABLE II. PERFORMANCE METRICS FOR YOLOV11N IMPLEMENTATION ON PYNQZ1 FPGA

| Estimated Value | LUT | FFs | DSP | BRAM | Throughput | FPS | Inference Time Per Image | Power Consumption | Power Efficiency |
|---|---|---|---|---|---|---|---|---|---|
| 70% of available LUTs | ✓ | | | | | | | | |
| 50% of available FFs | | ✓ | | | | | | | |
| 80% of available DSPs | | | ✓ | | | | | | |
| 8.3 Mbits of on-chip memory | | | | ✓ | | | | | |
| 100.33 GOP/s | | | | | ✓ | | | | |
| 18 FPS | | | | | | ✓ | | | |
| 55 ms | | | | | | | ✓ | | |
| 4.8 W | | | | | | | | ✓ | |
| 20.90 GOP/s/W | | | | | | | | | ✓ |

These metrics illustrate the effective deployment of YOLOv11s on the FPGA, offering high performance with energy efficiency suitable for real-time applications. This configuration is particularly well-suited for low-latency and low-power systems, making it an ideal solution for illegal mining activity detection, where timely and energy-efficient analysis of visual data is crucial for monitoring and intervention.

## VII. CONCLUSION

In this study, we conducted a comprehensive evaluation of YOLOv11n and YOLOv11s on the Illegal-mining-activities-aflkm dataset, assessing their classification accuracy, precision-recall balance, and overall detection capabilities. The results demonstrate that while both models exhibit strong performance in object detection, YOLOv11s consistently surpasses YOLOv11n in precision, recall, and mean average precision (mAP), making it the more reliable choice for high-accuracy applications. The superior performance of YOLOv11s underscores the impact of fine-tuning in adapting deep learning models to domain-specific challenges, particularly in detecting complex patterns associated with illegal mining activities. Furthermore, the reduced mean absolute error (MAE) in YOLOv11s signifies a more stable trade-off between precision and recall, ensuring higher consistency across various confidence thresholds. These findings highlight the critical role of model optimization in improving detection efficiency and minimizing misclassification errors.

Moreover, we have designed and implemented the architecture of YOLOv11 on the PynqZ1 FPGA, combining hardware and software optimizations for real-time monitoring in resource-constrained environments. This hardware-accelerated approach leverages the parallel processing capabilities of the FPGA, ensuring low-latency and energy-efficient detection, which is crucial for applications in illegal mining monitoring. Future research could explore further architectural refinements, dataset augmentation techniques, and real-world deployment scenarios to enhance the robustness and efficiency of these models. Additionally, integrating edge computing or lightweight versions of YOLOv11 on FPGA could enable real-time monitoring in remote or under-resourced areas, paving the way for scalable and proactive intervention strategies against illegal mining activities.

Future research can focus on several promising directions to enhance the robustness and deployment of YOLOv11-based systems for illegal mining detection. Architectural refinements, such as quantization, pruning, and model compression, could further optimize YOLOv11 for FPGA implementation, improving speed and energy efficiency. Expanding the dataset with synthetic data and varied environmental conditions would also improve model generalization in diverse real-world scenarios. Additionally, integrating edge computing with cloud-based analytics could enable large-scale, collaborative monitoring systems. Real-world deployment and testing in remote or harsh environments will be essential to validate performance and adaptability under operational constraints. Furthermore, developing lightweight, adaptive versions of YOLOv11 tailored for resource-limited IoT devices could expand its usability in under-resourced regions.

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# Healthcare 4.0: A Large Language Model-Based Blockchain Framework for Medical Device Fault Detection and Diagnostics

Khalid Alsaif*, Aiiad Albeshri, Maher Khemakhem, Fathy Eassa
Department of Computer Science, King Abdulaziz University, Jeddah 21589, Saudi Arabia

***Abstract*—This paper introduces a novel framework integrating Large Language Models (LLMs) with blockchain technology for medical device fault detection and diagnostics in Healthcare 4.0 environments. The proposed framework addresses key challenges, including real-time fault detection, data security, and automated diagnostics through a multi-layered architecture incorporating Internet of Things (IoT) integration, blockchain-based security, and LLM-driven diagnostics. Experimental evaluations demonstrate substantial improvements in diagnostic accuracy and response time while maintaining stringent security standards and regulatory compliance. The system provides enhanced fault detection with real-time monitoring capabilities and secure maintenance record management for smart healthcare. Comparative analysis of different LLMs and traditional Machine Learning (ML) methods shows that Deepseek-R1:7b achieved 97.6% classification accuracy, while O3-mini reached 90.4% and 91.2% in diagnosis accuracy and problem identification, respectively. Claude demonstrated the highest technical accuracy (98.4%), while Traditional ML excelled in processing time (11.7) and processing rate (10.68). Deepseek-R1:7b's offline capabilities ensure stringent security, privacy, and confidentiality with restricted connectivity, making it particularly suitable for sensitive healthcare applications where data protection is paramount.**

***Keywords*—Healthcare 4.0; Large Language Models; blockchain technology; medical device diagnostics; fault detection; smart healthcare; IoT healthcare security; machine learning**

## I. Introduction

The rapid advancement of healthcare technology has introduced Healthcare 4.0, an era defined by intelligent systems, interconnected medical devices, and data-driven decision-making. Medical devices play a critical role in this transformation, providing essential monitoring and treatment capabilities to enhance patient care. However, ensuring the reliability and safety of these devices remains a major concern, as device malfunctions can pose serious risks to patient health.

Recent developments in Internet of Things (IoT) technology have facilitated continuous monitoring of medical devices, generating vast volumes of operational data. While this data holds significant potential for fault detection and diagnostics, conventional monitoring systems often fail to deliver real-time, accurate diagnostics while maintaining data security and privacy compliance. The healthcare sector faces critical challenges in device maintenance, fault detection, and secure performance record management.

*Corresponding author.

Large Language Models (LLMs) [1] have recently emerged as powerful tools for complex pattern recognition and predictive analysis, introducing new opportunities for intelligent fault diagnostics. Meanwhile, blockchain technology provides an immutable, secure, and tamper-resistant data management system. However, the synergistic integration of LLMs and blockchain technology for medical device fault diagnostics remains largely unexplored.

In this research, we aim to address the following research questions:

- How can Large Language Models and blockchain technology be integrated to improve the accuracy of medical device fault diagnosis?
- Which models are most effective for diagnosing different types of medical device faults?
- How does blockchain integration affect the performance and security of the fault diagnosis system?
- What are the appropriate metrics for evaluating the effectiveness of a fault diagnosis system in the context of Healthcare 4.0?

These questions are particularly significant given the increasing complexity of medical devices, the critical nature of healthcare applications, and the stringent regulatory requirements governing healthcare data security and patient safety.

This paper proposes an innovative framework that leverages the analytical power of LLMs and the security features of blockchain technology to enhance medical device fault diagnostics. To address the first research question on LLM-blockchain integration, we develop a multi-layered architecture that enables secure data flow between IoT devices, blockchain networks, and LLM processing engines. For the second question on model effectiveness, we evaluate multiple LLM variants and traditional ML approaches across diverse fault scenarios. The third question regarding blockchain's impact is examined through comparative performance analysis with and without blockchain integration. Finally, we establish comprehensive evaluation metrics to address the fourth research question, measuring both technical performance and healthcare-specific requirements.

The key contributions of this study include:

*1) IoT-Blockchain-LLM integration:* A novel framework that combines real-time IoT monitoring, blockchain security, and LLM intelligence to ensure data immutability, fault detection accuracy, and optimal response times.

*2) Real-time processing framework:* A highly efficient processing system that demonstrates minimal blockchain overhead across diverse medical devices, validated through experiments on ECG monitors, insulin pumps, and defibrillators.

*3) Enhanced security and traceability:* A blockchain-based system that preserves fault history, provides immutable record-keeping, and ensures regulatory compliance while handling various fault types through comprehensive diagnostic tracking.

*4) Intelligent fault diagnostics:* The integration of LLMs enables detailed fault analysis, providing actionable insights for proactive maintenance in healthcare settings.

*5) Healthcare-specific implementation:* A practical, scalable solution designed to meet healthcare industry standards, ensuring regulatory compliance, performance optimization, and secure handling of diverse medical devices.

The remainder of this paper is structured as follows: Section II presents a comprehensive review of related work. Section III details the proposed framework architecture and its key components. Section IV describes the implementation and experimental setup and discusses the results and findings. Section V concludes the study and outlines future research directions.

## II. Literature Review

The rapid evolution of Healthcare 4.0 integrates IoT, AI, and blockchain technology, revolutionizing medical device management and fault diagnostics. Recent studies highlight the role of IoT-based monitoring in enhancing real-time device performance tracking, while blockchain ensures data integrity and security compliance. Additionally, Large Language Models (LLMs) have emerged as powerful tools for fault detection and predictive diagnostics, offering intelligent analysis and decision-making capabilities. However, existing research lacks a comprehensive framework that combines these technologies for secure, real-time, and automated medical device fault detection. This study addresses this gap by proposing an LLM-enhanced blockchain framework that ensures accurate diagnostics, data security, and regulatory compliance within Healthcare 4.0 environments.

### A. Healthcare 4.0 and Medical Device Management

Healthcare 4.0 integrates IoT, blockchain, artificial intelligence (AI), and additive manufacturing to revolutionize medical device management. Mrugalska et al. [2] demonstrated the application of open-source systems in dental engineering, while Karmakar et al. [3] introduced ChainSure, a blockchain-based insurance system for healthcare applications. In medical device logistics, Tu et al. [4] proposed a weighted density-based clustering model to optimize logistics operations. This work was complemented by Abusohyon et al. [5], who developed a fog network-based biosensor system to enhance real-time health monitoring. Additionally, Landolfi et al. [6] introduced digital twins for medical device value chain management, demonstrating their role in enhancing operational efficiency.

Cybersecurity in Healthcare 4.0 has also seen notable advancements. Gupta et al. [7] proposed a B2B healthcare security framework, which enhances data security and privacy protection in healthcare information management systems. Additionally, Szczepaniuk and Szczepaniuk [8] explored smart contract innovations that enhance secure medical transactions and healthcare compliance. The integration of AI and IoT in healthcare has enabled significant diagnostic improvements. Verma et al. [9] demonstrated the FCMCPS-COVID system, achieving a 98.8% diagnostic accuracy for COVID-19 detection using AI-powered IoT frameworks. To address privacy concerns, Rani et al. [10] introduced federated learning models tailored for Internet of Medical Things (IoMT) applications, which ensure secure patient data management. Similarly, Salim et al. [11] proposed a hybrid federated blockchain system to enhance data privacy and security in smart healthcare environments. For real-time patient monitoring, Mao et al. [12] developed triboelectric sensors integrated with deep learning models, improving wearable medical device performance. Additionally, Soffer et al. [13] identified adoption barriers in implementing Healthcare 4.0 solutions, emphasizing challenges related to technological integration and user acceptance. Meanwhile, Aranyossy and Halmosi [14] examined regulatory compliance challenges, highlighting the need for robust governance frameworks in Healthcare 4.0 adoption.

### B. Fault Detection and Diagnostics in Medical Devices

The field of medical device fault diagnostics has progressed from basic monitoring systems to advanced machine learning-based approaches. Anandhalekshmi et al. [15] contributed to this evolution by developing a hybrid diagnostic model, integrating the Baum-Welch algorithm with Support Vector Machine (SVM) to enhance sensor fault detection in healthcare monitoring systems.

Building on this foundation, Arfaoui et al. [16] introduced an innovative game-theoretic anomaly detection technique tailored for Wireless Body Area Networks (WBANs), improving fault detection efficiency in wearable medical devices.

More recently, Putra et al. [17] advanced the field by integrating federated learning with blockchain technology to develop a secure, decentralized fault detection system for IoT-based medical environments. Their study demonstrated notable improvements in diagnostic accuracy while reducing processing times, marking a significant breakthrough in real-time medical device diagnostics.

Alsaif et al. [18] introduced an LLM-based framework for fault detection in Industry 4.0, leveraging the Generative Pre-trained Transformer-4-Preview model, which inspires our application to healthcare, adapting its concepts for medical device diagnostics.

### C. Integration of AI with Traditional Methods

The integration of AI with traditional fault detection techniques has further enhanced diagnostic accuracy. Fang et al. [19] combined Simulated Annealing (SA) with Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to develop a robust fault detection framework. Similarly, Dash et al. [20] incorporated Self-Supervised Learning (SSL) with Bond Graph models, enhancing predictive fault detection capabilities. To improve fault isolation techniques, Han et al. [21] proposed a Dynamic Uncertain Causality Graph (DUCG)-based model, significantly enhancing fault classification accuracy. Al Shehri

et al. [22] developed a deep learning approach using convolutional neural networks and Darknet for COVID-19 detection from CT scans and X-ray images, achieving high accuracy, highlighting AI's role in diagnostics, which our study extends to device fault detection using LLMs. In industry-specific applications, Lv et al. [23] categorized fault detection and diagnosis (FDD) techniques for marine diesel engines, providing a systematic approach to engine fault analysis. Meanwhile, Montes-Romero et al. [24] achieved over 90% accuracy in photovoltaic system fault diagnostics, demonstrating the effectiveness of machine learning models in renewable energy applications.

The emergence of advanced architecture has further enhanced fault detection performance. Li et al. [25] introduced the Deep Expert Network, an interpretable AI model for transparent diagnostics, improving explainability in automated fault detection systems. Additionally, Zhao et al. [26] combined Multiscale Temporal Features (MTF) with Convolutional Neural Networks (CNNs), achieving a 93.75% accuracy rate in medical device fault detection. For real-time fault detection, Zhao et al. [27] developed an edge computing-based diagnostic system, reducing fault detection latency to 8 milliseconds, ensuring high-speed fault identification in time-sensitive healthcare applications. Similarly, Tang et al. [28] achieved 99.78% accuracy in real-time monitoring systems, demonstrating the potential of AI-driven fault prediction models in healthcare environments. Benchmarking studies have also contributed significantly to fault detection research. Bacha et al. [29] released a comprehensive Permanent Magnet Synchronous Motor (PMSM) fault dataset, providing a standardized evaluation framework for fault detection algorithms. Moreover, the dataset has supported Balachandran et al. [30] research on automated fault diagnostics, emphasizing the role of AI-driven methodologies in enhancing predictive maintenance systems.

### D. Blockchain and IoT Technology in Healthcare

The integration of blockchain and Internet of Things (IoT) technology in healthcare presents innovative solutions to address data security, privacy, and system scalability challenges. Kanwal et al. [31] proposed a chaos-based encryption system combined with blockchain technology to enhance medical image security, ensuring tamper-resistant storage and transmission. Meanwhile, Guerar et al. [32] introduced a Self-Sovereign Identity (SSI)-based system designed to prevent fraud and maintain cross-border interoperability, facilitating secure patient identity management across healthcare networks. Almalki et al. [33] proposed a prototype model integrating blockchain with IoMT devices, demonstrating its potential for secure healthcare data management by collecting IoMT data over edge computing gateways and broadcasting it across peer nodes using smart contracts, which supports our framework's use for fault history integrity.

For distributed healthcare architectures, Wang et al. [34] integrated blockchain with edge computing, enhancing secure health data management and reducing latency in decentralized healthcare systems. Additionally, Liu et al. [35] developed a blockchain-based incentive mechanism to promote data sharing and security within smart healthcare environments. Additionally, Liu et al. [36] developed a blockchain-based incentive mechanism to promote data sharing and security within smart healthcare environments. Similarly, Li et al. [37] focused on enhancing interoperability, leveraging blockchain technology to improve data exchange efficiency among heterogeneous healthcare systems.

Beyond patient data security, blockchain plays a critical role in healthcare supply chain management. Yadav et al. [38] examined the adoption barriers to blockchain-based vaccine distribution, identifying challenges in scalability, regulatory compliance, and stakeholder adoption. Moreover, Mangala et al. [39] proposed an IoT-integrated blockchain model to ensure pharmaceutical tracking transparency, mitigating the risks of counterfeit drugs in global supply chains. Emerging trends in blockchain technology also highlight security enhancements. Liu et al. [40] introduced quantum-resistant frameworks, addressing potential post-quantum cybersecurity threats in medical data protection. Additionally, Mershad [41] developed lightweight blockchain architectures optimized for resource-constrained IoT medical devices, reducing computational overhead while maintaining data security.

### E. Large Language Models for Fault Detection

The application of Large Language Models (LLMs) in healthcare fault diagnostics represents an emerging area of research. While LLMs have yet to be fully implemented in medical device fault detection, advancements in related fields highlight their potential applications. Kumar et al. [42] laid the foundational work in this domain by developing an ensemble learning framework. Although their study did not specifically involve LLMs, it demonstrated the capabilities of advanced AI models in healthcare security and fault diagnostics.

Recent developments indicate LLMs' adaptability for fault detection and diagnosis across various industrial sectors. Zheng et al. [43] demonstrated that fine-tuned LLMs can achieve high diagnostic accuracy, particularly when employing data normalization techniques and handling missing values efficiently. In intelligent manufacturing, Zhang et al. [44] highlighted the role of LLMs in enhancing human-machine collaboration and improving service-level fault detection capabilities. Similarly, Mustapha [45] explored domain-specific LLMs, showing their ability to detect subtle fault signatures in mechanical systems, paving the way for highly specialized diagnostic models.

Beyond fault diagnostics, researchers are investigating the broader implications of LLMs in AI-driven healthcare advancements. Liu et al. [46] conducted a comprehensive survey on ChatGPT-related advances, analyzing pre-training methodologies and instruction fine-tuning techniques to enhance LLM adaptability. Meanwhile, Singh et al. [47] developed a strategic roadmap for generative AI applications, employing text-mining techniques and structural topic modeling to optimize LLM-based knowledge extraction in medical fault analysis.

### F. Research Gaps

Based on the comprehensive review of existing literature, several gaps have been identified in current research. Table I presents a comparative analysis of existing solutions versus our proposed framework.

A thorough analysis of existing literature has revealed multiple research gaps in medical device fault diagnostics, particularly in areas such as real-time fault detection, blockchain

TABLE I. COMPARATIVE ANALYSIS OF FEATURES IN HEALTHCARE DEVICE FAULT DIAGNOSTICS

| Features/Capabilities | [15] | [16] | [48] | [17] | [43] | Proposed Framework |
|---|---|---|---|---|---|---|
| Real-time Fault Detection | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Blockchain Security | × | ✓ | ✓ | ✓ | × | ✓ |
| LLM Utilization | × | × | × | × | ✓ | ✓ |
| Automated Diagnostics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Data Privacy | × | × | ✓ | ✓ | ✓ | ✓ |
| IoT | ✓ | ✓ | × | ✓ | × | ✓ |

security, AI-driven automation, and IoT integration. While previous studies have made strides in specific aspects of fault diagnostics, critical limitations remain in ensuring data security, scalability, interoperability, and advanced AI-driven fault detection methods.

One of the primary gaps identified is the lack of Large Language Model (LLM) utilization for fault diagnostics. Existing approaches primarily rely on traditional machine learning algorithms without leveraging LLMs for contextual data analysis and predictive diagnostics. As seen in Table II, none of the referenced studies except the proposed framework have integrated LLMs for enhanced fault detection and decision-making. The proposed framework fills this gap by incorporating LLM-based intelligence and improving anomaly detection, fault prediction, and adaptive learning capabilities.

Another key gap is blockchain security in fault diagnostics. While studies [17] and [43] incorporate blockchain technology, others lack secure, decentralized data management mechanisms. Without blockchain, fault detection logs remain vulnerable to tampering, compromising data integrity and compliance with healthcare regulations. The proposed framework ensures end-to-end security through blockchain-based immutable logs, decentralized verification, and automated compliance auditing.

Additionally, real-time fault detection mechanisms are not consistently integrated across existing models. Studies [15], [16], and [48] provide real-time monitoring, but studies [17] and [43] do not emphasize real-time data processing and fault resolution. The proposed framework addresses this limitation by leveraging IoT-enabled real-time monitoring, ensuring faults are detected and mitigated instantly with minimal latency.

Furthermore, current frameworks lack full IoT integration, limiting their ability to aggregate, analyze, and process real-time data from multiple medical devices. As shown in Table I, none of the referenced studies have effectively integrated IoT-based fault detection, leading to gaps in real-time device communication and predictive maintenance. The proposed framework fully integrates IoT with AI and blockchain, enabling seamless connectivity and automated diagnostics across healthcare infrastructures.

Finally, data privacy and compliance mechanisms remain insufficiently addressed. While some studies implement basic privacy protocols, they do not fully incorporate federated learning for secure AI model training or blockchain for compliance tracking. The proposed framework strengthens privacy protection by utilizing federated learning, ensuring secure AI training across multiple healthcare institutions without sharing sensitive patient/device data.

## III. METHODOLOGY

Our methodology presents an innovative approach to Healthcare 4.0 by seamlessly integrating three core Industry 4.0 technologies—Artificial Intelligence, Blockchain, and the Internet of Things (IoT). The framework leverages Large Language Models as the AI component to provide sophisticated pattern recognition and automated diagnostic capabilities for medical device fault detection. IoT technology enables comprehensive real-time monitoring and data collection from medical devices through sensors and edge computing nodes, ensuring continuous device health assessment. Blockchain technology is the foundation for secure data management, providing immutable record-keeping and ensuring the integrity of diagnostic results while maintaining health authority compliance. These three technologies work in concert within our six-layer architecture: IoT handles data acquisition and device monitoring, AI processes and analyses the collected data for fault detection, and blockchain secures and validates all system operations. This integrated approach creates a robust, secure, and intelligent framework that addresses the complex requirements of modern healthcare environments while enabling automated, reliable, and traceable medical device diagnostics.

### A. Framework Overview

The Healthcare 4.0 Fault Diagnosis Framework, as illustrated in Fig. 1, provides a comprehensive solution for medical device monitoring and fault detection through a six-layer interconnected architecture. Each layer plays a distinct yet integrated role, ensuring intelligent diagnostics, real-time monitoring, data security, and seamless interoperability.

The Data Source Layer serves as the foundation of the framework, comprising two key components. The Data Collection component aggregates information from diverse sources, including academic journals, social media platforms, and authoritative healthcare organizations. Simultaneously, the Data Acquisition component interfaces directly with medical devices, raw sensors, and Electronic Health Records (EHR) systems, ensuring real-time operational data retrieval for fault detection and analysis.

At the core of the framework, the Intelligence Layer is responsible for advanced analytical processing. This layer integrates a knowledge base to store domain expertise, decision-making capabilities to generate actionable insights, and a diagnostic system to identify faults. Additionally, Generative AI techniques enhance pattern recognition and predictive analytics, allowing for early fault detection and anomaly prediction. This layer works closely with the Data Storage Layer, which combines cloud-based and on-premise storage solutions to ensure scalability, data redundancy, and secure access to diagnostic information.

The Security Layer provides comprehensive protection through three key mechanisms. Blockchain technology ensures immutable record-keeping, maintaining transparent, tamper-proof logs of system activities and device states. Access control mechanisms regulate user permissions based on roles and authorization levels, preventing unauthorized access to sensitive data. Additionally, data encryption safeguards all system interactions, securing device readings, diagnostic results, and patient records against potential cyber threats.

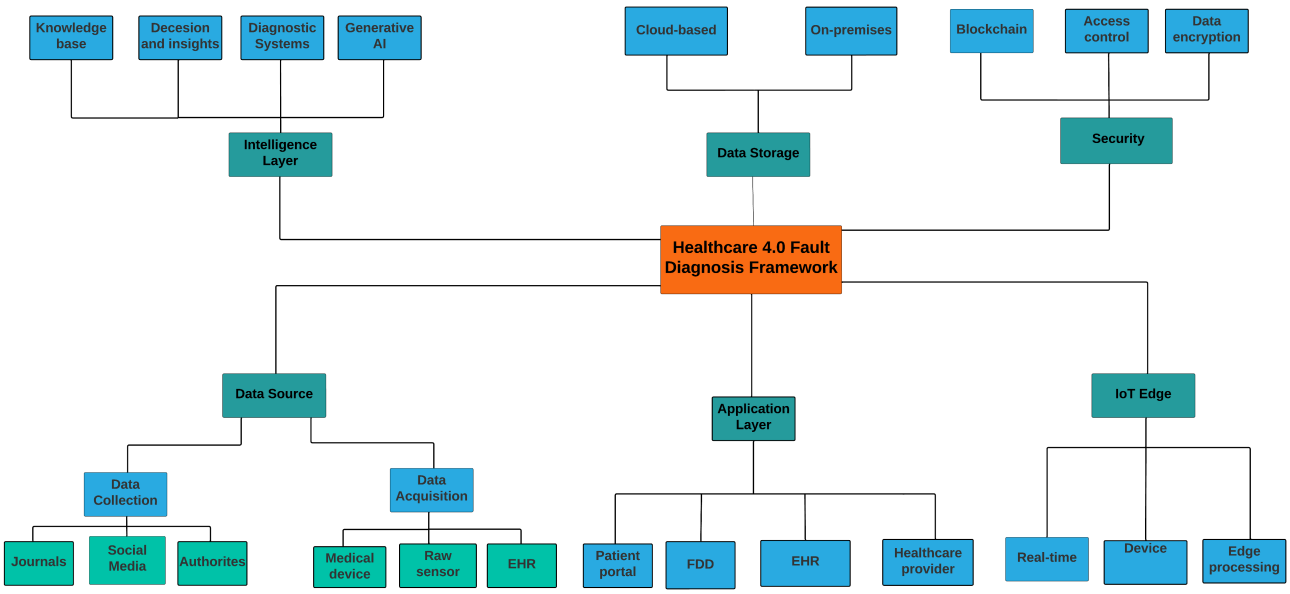



Fig. 1. Healthcare 4.0 fault diagnosis framework layers.

The IoT Edge Layer manages the critical interface between physical medical devices and the digital diagnostic framework. This layer facilitates real-time data processing, efficient device communication, and seamless integration with the broader system. It incorporates device management capabilities, supports low-latency fault detection, and enables edge computing functionalities, ensuring that critical diagnostic operations are performed with minimal delay.

The Application Layer serves as the central interface for all healthcare stakeholders. It enables healthcare providers to access comprehensive device insights and patient data through an interactive patient portal. Additionally, the Fault Detection and Diagnosis (FDD) module delivers detailed diagnostic insights, enhancing medical decision-making. EHR system integration ensures synchronized patient care coordination, bridging the gap between fault diagnostics and clinical workflows.

The modular and hierarchical architecture of the framework allows each layer to function independently while ensuring seamless interoperability across components. This design approach enhances scalability, security, and operational efficiency, making the framework highly adaptable for future advancements in medical device fault diagnostics and Healthcare 4.0 solutions.

### B. System Architecture

The system architecture, illustrated in Fig. 2, is designed to support medical device fault diagnostics by integrating six key interconnected components: Data Acquisition, IoT, Blockchain, Data Storage, Intelligence, and Applications. This multi-layered architecture ensures scalability, security, and real-time processing, allowing seamless collaboration between healthcare providers, diagnostic systems, and medical devices.

The Data Acquisition component forms the foundation, incorporating two main streams: device-based inputs and knowledge-based inputs. The device stream includes data from technicians through medical devices, patients through wearable devices, and Electronic Health Records (EHR). The knowledge stream integrates academic and research knowledge through established databases like Scopus, IEEE, and other authoritative sources, enriching the knowledge base for diagnostic analysis.

The IoT layer processes incoming data through an IoT Core component that standardizes and preprocesses data from various sources before transmission. This connects to the Blockchain component, which implements distributed ledger technology through multiple nodes to ensure data integrity and secure transmission throughout the system.

The Data Storing layer comprises three key elements: Cloud-DB for structured operational data, a specialized Knowledge Base system that supports the LLM processing, and a secondary Cloud-DB for backup and redundancy. This robust storage architecture ensures data availability and reliability while maintaining system performance.

The Intelligence layer features dual LLM implementations: a Maintenance Support System LLM for technical diagnostics and a Medical LLM for clinical insights. This dual-LLM approach enables sophisticated pattern recognition and diagnostic analysis across technical and medical domains.

The Applications layer provides comprehensive functionality through FDD (Fault Detection and Diagnosis) for identifying and analyzing device issues, MDS (Medical Diagnosis System) for clinical decision support, Text Generation for automated reporting and documentation, and EHR integration for comprehensive patient record management.

The entire system is accessible to stakeholders through web and mobile applications, ensuring healthcare practitioners, device technicians, and patients can access critical information and diagnostics through multiple interfaces. This multi-modal access approach enhances system usability while maintaining

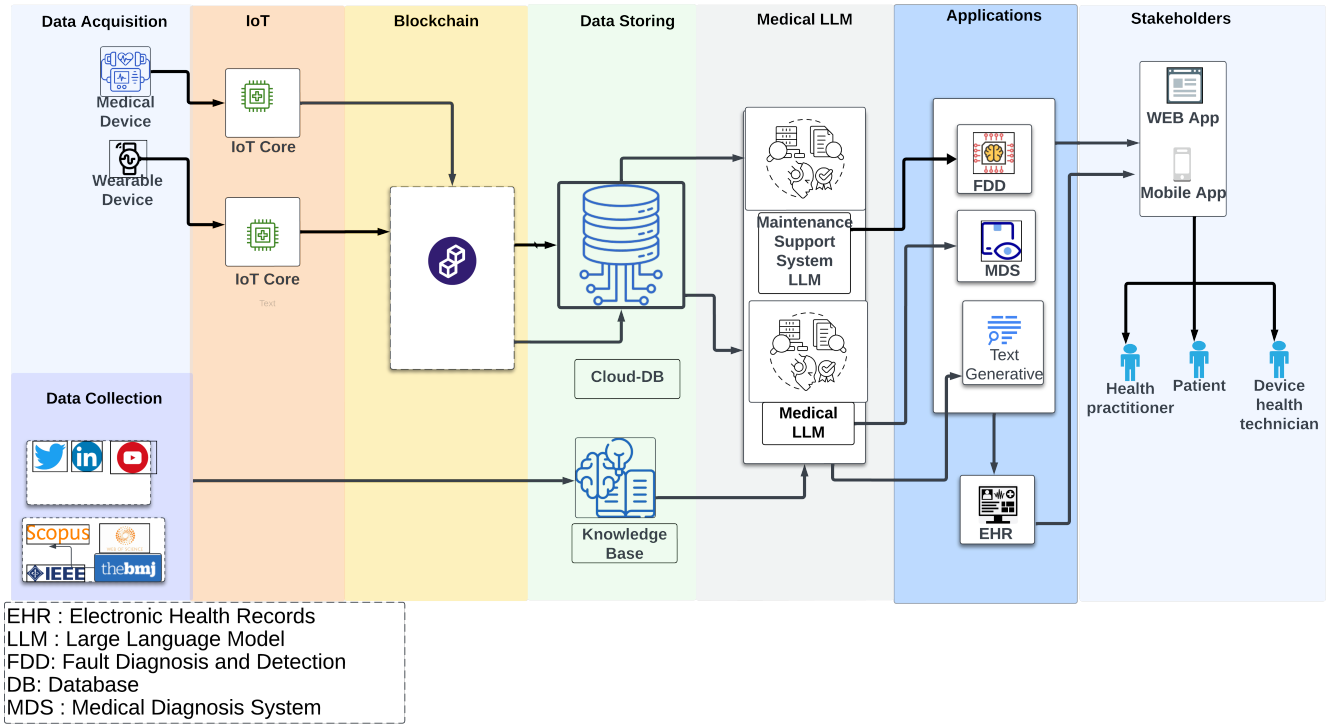



Fig. 2. System architecture for healthcare 4.0 medical device fault diagnostics framework.

security through appropriate access controls and authentication mechanisms.

The proposed architecture emphasizes scalability, security, and integration capabilities, ensuring the system can adapt to evolving healthcare technology needs while maintaining robust fault diagnostic capabilities. The combination of blockchain security, LLM intelligence, and comprehensive data management creates a powerful platform for advancing medical device maintenance and healthcare delivery.

In the Data Layer, we implement AWS IoT Core simulation to systematically collect and classify fault data according to the classification system defined in Table II. The simulation framework generates device fault scenarios at 5-second intervals across medical devices, replicating the four fault categories - power system (E101), sensor system (E102), thermal management (E103), and communication (E104). Each fault type is generated according to its specified criticality level in Table II, with critical faults (E101 and E103) receiving prioritized handling over high-priority faults (E102 and E104). Virtual devices, including ECG monitors, insulin pumps, defibrillators, and thermometers, transmit standardized fault messages via MQTT protocol, maintaining the fault distribution patterns and criticality.

TABLE II. MEDICAL DEVICE FAULT CLASSIFICATION SYSTEM

| Fault Code | Category | Description | Criticality Level |
|---|---|---|---|
| **E101** | Power System | Battery failure | Critical |
| **E102** | Sensor System | Sensor malfunction | High |
| **E103** | Thermal Management | Overheating | Critical |
| **E104** | Communication | Data transmission errors | High |

### C. Core Blockchain Architecture

The blockchain architecture employs a hierarchical block structure incorporating four essential components, as shown in Fig. 3: block indexing, temporal stamping, diagnostic data payload, and cryptographic hash values. Each block maintains a secure link to its predecessor through SHA-256 hash functions, ensuring data immutability and chain integrity while maintaining health authority compliance requirements.

[{"index": 0, "timestamp": 1720905190.9940019, "data": "Genesis Block", "previous_hash": "0", "hash": "13140a7eb4be9268995e96b4dab52bb54bcda61c6bc8cf650e1475b20f59c05c"}]

Fig. 3. Block structure.

The security architecture implements a multi-layered approach utilizing AWS IoT Core's security features. The system employs as shown in Table III:

TABLE III. SECURITY IMPLEMENTATION METRICS

| Security Feature | Implementation Method |
|---|---|
| Authentication | TLS Certificates |
| Data Encryption | AES-256 |
| Access Control | Role-Based |
| Message Integrity | SHA-256 |

This comprehensive implementation demonstrates the framework's capability to handle diverse fault scenarios across

multiple medical devices while maintaining strict security protocols and real-time performance requirements. The system's ability to process and record faults with sub-millisecond latency while maintaining 100% message delivery reliability makes it suitable for critical healthcare environments. The balanced distribution of fault detection across different device types and fault categories indicates robust monitoring capabilities, which are essential for maintaining patient safety and device reliability in healthcare settings.

### D. IoT Integration

The IoT integration methodology in our Healthcare 4.0 framework establishes a systematic approach to medical device monitoring and fault detection. This methodology focuses on creating a reliable, secure, and scalable foundation for real-time device data collection and analysis.

Our framework implements a three-tiered hierarchical communication protocol utilizing MQTT over TLS 1.2 for secure medical device interactions. The device layer establishes standardized data packets containing all medical equipment's fault codes, operational metrics, and status information. These packets follow a unified format for consistent monitoring and analysis. The intermediate layer employs edge nodes for data aggregation and optimization, implementing dynamic transmission frequencies based on device criticality and operational status. At the core system layer, a routing algorithm manages communication flow, ensuring immediate transmission of critical faults while optimizing routine monitoring data through standard channels.

The data collection methodology incorporates an IoT sensor simulation system replicating real-world medical device fault scenarios. The simulation environment generates four primary fault types across critical medical devices: battery failures (E101), sensor malfunctions (E102), thermal issues (E103), and communication errors (E104). Each device generates fault data at consistent 5-second intervals, providing real-time monitoring capabilities.

Our testing environment processes approximately 720 fault messages per hour per device, with each message containing detailed fault parameters, including device type, fault code, timestamp, and fault description. The system implements AWS IoT Core for message handling, utilizing MQTT protocols for reliable data transmission. This approach ensures consistent data collection while maintaining the ability to simulate concurrent fault scenarios across multiple devices, providing a robust testing environment for our diagnostic framework.

### E. LLM Utilization

Our framework integrates LLMs with blockchain for medical device fault diagnostics through a structured prompt engineering approach, as shown in Fig. 4. The system processes blockchain fault data entries in Fig. 5 containing critical parameters such as fault_code 'E101', device_type 'ECG Monitor,' and fault description 'Battery failure,' with secure hash verification to ensure data integrity.

The diagnostic workflow transforms blockchain data into expert-system prompts, as shown in Fig. 5, enabling contextual analysis of device faults. System performance is quantified through our confidence scoring mechanism:

```
prompt = f"""
As a medical device expert, please analyze this fault:
Device Type: {fault_data['device_type']}
Fault Code: {fault_data['fault_code']}
Description: {fault_data['description']}

Provide a detailed diagnosis and recommended actions.
"""
```

Fig. 4. Fault diagnostics prompt.

Block added to blockchain: {'index': 19408, 'timestamp': 1736516335.509967, 'data': {'fault_code': 'E101', 'device_type': 'ECG Monitor', 'timestamp': '2025-01-10T13:38:55Z', 'description': 'Battery failure'}, 'previous_hash': 'daeec3b2dd93621d61eb0f3fe90295e82c698bb0634286d6d68f8c3b66832680', 'hash': '93d306bad8f5106b1559fce5f446e9e5022d367d9a38643b560f827f72197641'}

Fig. 5. Blockchain data.

### F. Model Configuration and Implementation Parameters

To comprehensively address our second research question regarding model effectiveness for medical device fault diagnostics, we implemented multiple AI approaches with specific configurations designed to optimize diagnostic performance while maintaining computational feasibility.

*1) Large language model configurations:* The LLM implementations were configured with parameters tuned for medical device fault analysis:

TABLE IV. LARGE LANGUAGE MODEL CONFIGURATION PARAMETERS

| Parameter | Claude 3.7 Sonnet | Deepseek-R1:7B | O3-mini | Grok-2 |
|---|---|---|---|---|
| Model ID | claude-3-7-sonnet-20250219 | deepseek-coder:6.7b | o3-mini | gpt-4-turbo-preview |
| Temperature | 0.1 | 0.7 | 0.7 | 0.1 |
| Max Tokens | 4000 | 2000 | 2000 | 2000 |
| API Interface | Anthropic API | Ollama (Local) | OpenAI API | Grok API |
| Deployment | Cloud-hosted | Edge device | Edge device | Cloud-hosted |

Each LLM (Table IV) was prompted with a structured template designed to extract fault classifications and diagnostic explanations.

*2) Traditional machine learning configuration:* The traditional ML approach (Table V) implemented a text classification pipeline with the following configuration:

These configuration parameters were selected based on preliminary performance testing to optimize the balance between diagnostic accuracy and computational efficiency across diverse medical device types and fault scenarios.

### G. Dataset Description

A comprehensive dataset was collected through IoT device simulation during a specific timeframe (December 31, 2024, 10:24:18Z to 10:45:13Z). The dataset in Table VI encompasses 245 distinct fault events distributed across four critical medical device categories, providing a robust foundation for system

TABLE V. TRADITIONAL ML CONFIGURATION PARAMETERS

| Component | Configuration |
|---|---|
| Text Vectorization | TF-IDF Vectorizer (max_features=500) |
| Classification Algorithm | Random Forest (n_estimators=100, random_state=42) |
| Data Split | Train-test split (test_size=0.2, random_state=42) |
| Input Features | Combined fault description and suggested remedy text |
| Output Classes | Four fault categories (Power, Sensor, Thermal, Communication) |

evaluation and performance analysis. The data collection methodology implemented consistent 5-second intervals using the MQTT protocol with QoS level 0, achieving a 100% transmission success rate and sub-millisecond processing times.

The dataset exhibits a balanced distribution of fault events across device types, with defibrillators representing 33.5% (82 events), thermometers at 24.9% (61 events), ECG monitors at 23.7% (58 events), and insulin pumps at 17.9% (44 events). Each fault record maintains a standardized JSON structure containing essential attributes, including device type, fault code, timestamp in ISO 8601 format, and detailed fault description. The fault categories demonstrate natural distribution patterns, encompassing battery failures (E101, 27.8%), sensor malfunctions (E102, 23.3%), thermal issues (E103, 22.0%), and communication errors (E104, 26.9%).

TABLE VI. DEVICE MONITORING DISTRIBUTION

| Device Type | Total Faults | Percentage | Most Common Fault |
|---|---|---|---|
| Defibrillator | 82 | 33.5% | E104 (Communication) |
| ECG Monitor | 58 | 23.7% | E102 (Sensor) |
| Thermometer | 61 | 24.9% | E101 (Battery) |
| Insulin Pump | 44 | 17.9% | E104 (Communication) |

Based on the implementation data collected, the system demonstrated comprehensive monitoring capabilities across multiple device types, as shown in Table VI.

*1) Fault distribution analysis:* Analysis of 245 fault events revealed the following distribution patterns, as shown in Table VII and Fig. 6:

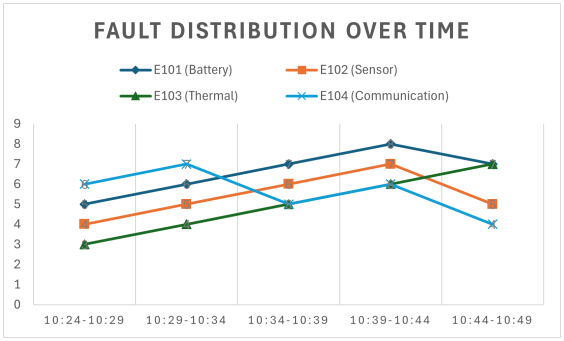
TABLE VII. FAULT TYPE DISTRIBUTION

| Fault Type | Occurrence Count | Percentage | Primary Affected Device |
|---|---|---|---|
| E101 (Battery) | 68 | 27.8% | ECG Monitor |
| E102 (Sensor) | 57 | 23.3% | Thermometer |
| E103 (Thermal) | 54 | 22.0% | Defibrillator |
| E10 (Communication) | 66 | 26.9% | Defibrillator |

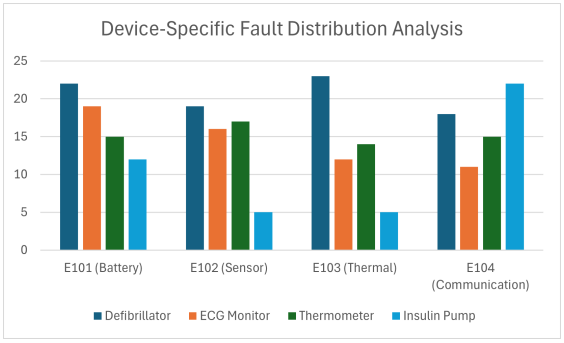
*2) Real-time performance metrics:* The system's real-time performance characteristics were tested using 245 messages from AWS IoT sensors, with results summarized, as shown in Table VIII:

The metrics are defined as follows:

- Message Processing Time $(T_{proc})$ :




(a)




(b)

Fig. 6. Fault distribution: (a) Fault distribution over time, showing the occurrence of different fault types at various time intervals. (b) Device-specific fault distribution analysis, illustrating the frequency of fault occurrences across different medical devices.

TABLE VIII. PERFORMANCE METRICS (BASED ON 245 MESSAGES)

| Metric | Value | Performance Level |
|---|---|---|
| Message Processing Time | <1ms | Optimal |
| Message Interval | 5 seconds | Consistent |
| Data Transmission Success Rate | 100% | Optimal |
| Blockchain Update Time | <1s | Optimal |

The time taken to ingest, validate, and process a sensor message through the blockchain-LLM pipeline is Eq. 1:

$$T_{proc} = \frac{1}{N} \sum_{i=1}^{N} (t_{out,i} - t_{in,i}) \tag{1}$$

- Timestamp when the message $t_{in,i}$ enters the system
- Timestamp when the message $t_{out,i}$ is confirmed on the blockchain and diagnosed by the LLM $T_{\text{proc}} < 1$ ms (optimal), achieved via parallelized blockchain validation and LLM caching.

## IV. RESULTS

This study presents a comprehensive comparison of five distinct AI models for medical device fault diagnosis, evaluating their performance across multiple metrics as summarized in Table IX.

TABLE IX. COMPARATIVE PERFORMANCE OF AI MODELS FOR MEDICAL DEVICE FAULT DIAGNOSIS

| Metrics | Diagnosis Model | | | | |
|---|---|---|---|---|---|
| | Claude 3.7 sonnet | Deepseek-R1:7B | O3-mini | Grok-2-latest | Traditional ML |
| | Evaluation Model | | | | |
| | GPT-4 Turbo | Claude-3-sonnet-20240229 | | | |
| Classification Accuracy (%) | 96.8 | 97.6 | 95.2 | 95.2 | 92.0 |
| Diagnosis Accuracy (%) | 79.2 | 84.8 | 90.4 | 60.0 | 73.6 |
| Core Problem Identification (%) | 79.2 | 85.6 | 91.2 | 66.4 | 73.6 |
| Technical Accuracy (%) | 98.4 | 94.4 | 97.6 | 78.4 | 85.6 |
| Processing Time (min) | 45.5 | 35.2 | 34.8 | 17.0 | 11.7 |
| Processing Rate (cases/min | 2.75 | 3.55 | 3.59 | 7.35 | 10.68 |
| Model Type | LLM | LLM | LLM | LLM | Random Forest, TF-IDF, KNN |
| Errors | None reported | One misclassification | Few misclassifications | Two misclassifications | Classification errors |

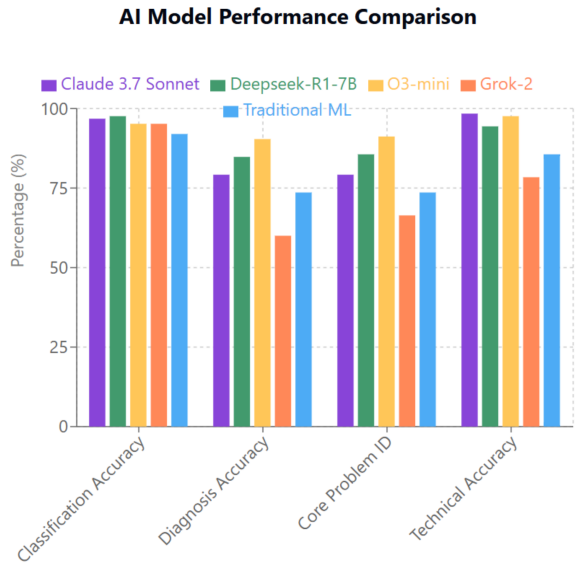



Fig. 7. Performance comparison of five AI diagnostic approaches across key metrics.

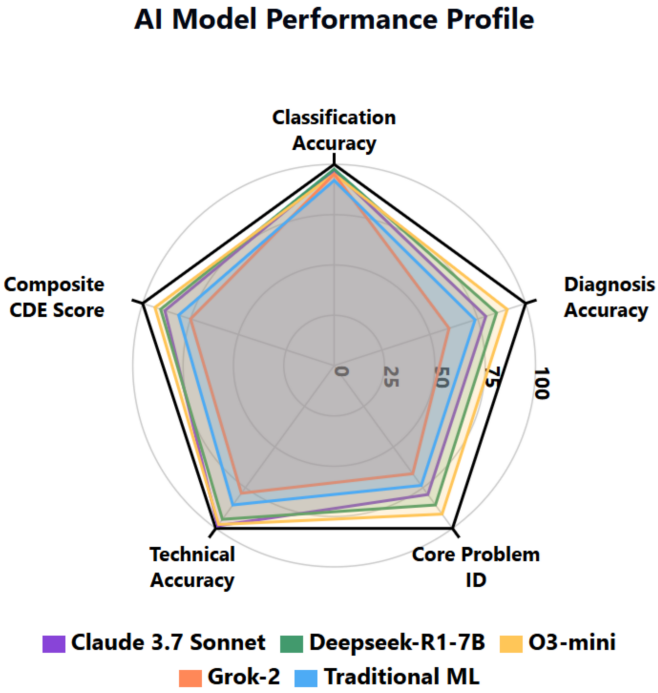



Fig. 8. AI model performance profile.

## V. DISCUSSION

The comparative analysis provides valuable insights into each model's strengths, limitations, and optimal application contexts for medical device fault diagnostics.

### A. Performance Comparison and Distinctive Characteristics

The experimental results reveal significant performance variations between the evaluated models. As illustrated in Fig. 7, the O3-mini model demonstrates superior diagnostic capabilities, achieving the highest diagnosis accuracy (90.4%) and core problem identification (91.2%). Deepseek-R1-7B follows with robust performance across all metrics (classification accuracy: 97.6%, diagnosis accuracy: 84.8%, core problem identification: 85.6%), positioning it as a strong contender. Claude 3.7 Sonnet excels in technical accuracy (98.4%) but shows more moderate performance in diagnosis accuracy (79.2%) and core problem identification (79.2%). Grok-2 presents high classification accuracy (95.2%) but considerably lower diagnostic capabilities (diagnosis accuracy: 60.0%, core problem identification: 66.4%). The traditional ML approach demonstrates balanced performance (classification accuracy: 92.0%, diagnosis accuracy: 73.6%, core problem identification:

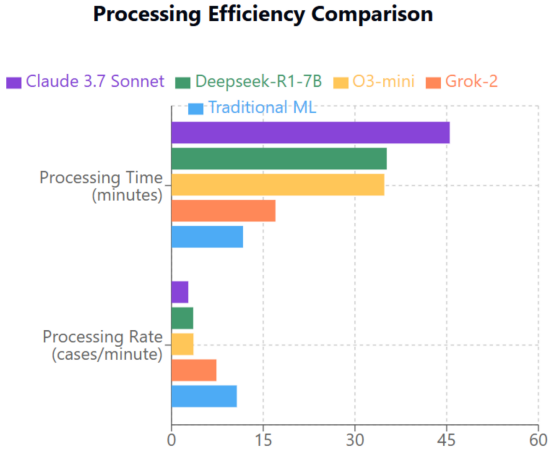



Fig. 9. Comparison of processing time and rate across diagnostic systems.

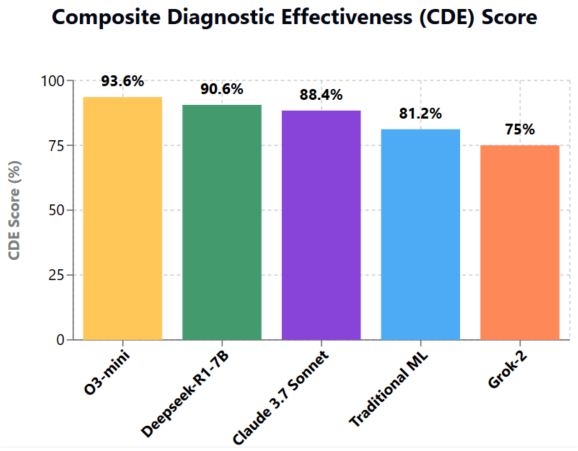



Fig. 10. Composite Diagnostic Effectiveness (CDE) score.

73.6%) with exceptional processing efficiency.

The radar chart in Fig. 8 effectively visualizes these multidimensional performance profiles, highlighting the unique strengths of each approach. The O3-mini model exhibits the most balanced performance across all metrics, while Grok-2 shows pronounced variability between its classification and diagnostic capabilities. This superior diagnostic performance can be attributed to its balanced architecture, which appears optimized for both fault classification and root cause analysis. When examining the Composite Diagnostic Effectiveness (CDE) score, calculated as:

$$CDE = (\alpha \times CA + \beta \times DA + \gamma \times CPI + \delta \times TA)/(\alpha + \beta + \gamma + \delta)$$

Where:

CDE = Comprehensive Diagnostic Effectiveness

$\alpha, \beta, \gamma, \delta$ = weighting factors

CA = Classification Accuracy

DA = Diagnosis Accuracy

CPI = Core Problem Identification

TA = Technical Accuracy

Assume equal weights ($\alpha = \beta = \gamma = \delta = 1$) The Composite Diagnostic Effectiveness (CDE) scores in Figure 4 quantitatively summarize these differences, with O3-mini (93.6%) and Deepseek-R1-7B (90.6%) demonstrating the highest overall effectiveness.

### B. Evaluation Methodology and Metrics

We chose Claude 3 Sonnet as the universal evaluator for all models to ensure that the methods were consistent and that the comparisons were fair. This creates a standard evaluation framework that eliminates any possible differences in assessment criteria that could come up if different evaluators were used for each model. As a leading language model with proven abilities in technical analysis and evaluation, Claude 3 Sonnet served as a standard against which all diagnostic outputs were measured.

The evaluation metrics were operationalized as follows:

*1) Diagnosis Accuracy (DA):* Measured as the percentage of cases where the model correctly identified the specific fault mechanism, as verified against ground truth data. This metric quantifies the model's ability to pinpoint the exact cause of device malfunction.

*2) Core Problem Identification (CPI):* Assessed as the percentage of cases where the model correctly identified the fundamental issue category, even if specific mechanism details varied from ground truth. This metric evaluates broader diagnostic categorization accuracy.

*3) Technical Accuracy (TA):* Determined by evaluating the correctness and precision of technical descriptions provided in the diagnostic report. This metric measures the model's ability to accurately describe fault mechanisms in technically sound terms.

*4) Classification Accuracy (CA):* Calculated as the percentage of correctly classified fault types (e.g., power issue, sensor issue, thermal issue) compared to ground truth labels.

These metrics collectively provide a multifaceted assessment of each model's diagnostic capabilities, as illustrated in Fig. 7.

### C. Processing Efficiency and Practical Implications

Fig. 9 highlights substantial differences in processing efficiency between the models. Traditional ML demonstrates exceptional processing speed (10.68 cases/minute), followed by Grok-2 (7.35 cases/minute), while LLM-based approaches show more moderate processing rates (O3-mini: 3.59, Deepseek-R1-7B: 3.55, Claude 3.7 Sonnet: 2.75 cases/minute). These differences have significant implications for practical deployment, particularly in time-sensitive diagnostic contexts. The Efficiency-Adjusted Performance (EAP) metric is calculated as:

EAP = CDE × (cases/minute)

Provides insight into the efficiency-accuracy trade-off. Traditional ML achieves the highest EAP (867.22), suggesting its utility in high-volume scenarios despite the lower raw accuracy. Conversely, while Claude 3.7 Sonnet provides the most technically accurate explanations, its lower processing rate results in the lowest EAP (243.10), potentially limiting its applicability in time-sensitive contexts.

### D. Deployment Considerations and Security Implications

A noteworthy feature of Deepseek-R1-7B is its capability to function as an offline, local model, offering significant advantages for applications with stringent security and privacy requirements. This offline deployment capability makes it particularly suitable for medical settings where patient data confidentiality is paramount and network connectivity may be restricted. Its strong performance (CDE: 90.6%, Fig. 10) combined with local deployment capabilities positions Deepseek-R1-7B as an ideal solution for medical environments with heightened data security considerations. The capability to maintain high diagnostic accuracy (84.8%) without external data transmission represents a valuable characteristic in sensitive healthcare applications.

Similarly, the traditional ML approach offers offline deployment advantages with exceptional processing efficiency, as shown in Fig. 9. This combination of local operation and high throughput may be particularly valuable in resource-constrained environments or emergency scenarios requiring rapid diagnostic assessment.

### E. Diagnostic Consistency and Error Analysis

The Diagnostic Precision Gap (DPG) is calculated as:

DPG = CA - DA

provides insight into each model's consistency between classification and diagnosis. O3-mini demonstrates the smallest gap (4.8%), indicating highly consistent performance in both tasks. In contrast, Grok-2 shows a substantial gap (35.2%), suggesting a significant discrepancy between its ability to classify fault types and diagnose specific causes. Analysis of error patterns reveals that Deepseek-R1-7B and O3-mini demonstrate the most robust fault differentiation capabilities, while Grok-2 shows systematic misclassifications, particularly confusing sensor issues with power issues. These patterns are visible in the performance metrics displayed in Figs. 7 and 8, highlight important considerations for deployment in critical diagnostic applications.

The comprehensive evaluation framework established in this study, supported by the visualizations in Figures 7–10, provides a systematic basis for model selection in medical device fault diagnostics. While O3-mini and Deepseek-R1-7B offer superior diagnostic accuracy for applications prioritizing precision, traditional ML and Grok-2 provide advantages in processing efficiency for high-volume scenarios. This analysis establishes a foundation for selecting appropriate AI models based on the specific requirements and constraints of medical device fault diagnostic applications.

### F. Results Highlights

From the above discussion and encouraging results, it is clear that this research work introduced a Healthcare 4.0 framework that integrates IoT, blockchain, and LLMs to revolutionize medical device fault diagnostics. The study's outcomes directly align with its core contributions, demonstrating a secure, intelligent, and efficient solution for medical device management.

*1) IoT-Blockchain-LLM integration:* The successful integration of IoT, blockchain, and LLMs has been validated through real-time fault detection across ECG monitors, insulin pumps, and defibrillators, as evidenced by performance metrics showing sub-millisecond message processing times and 100% data transmission success (Table VI). This synergy ensures accurate diagnostics with blockchain adding minimal overhead (0.1227 seconds), fulfilling the promise of a robust, real-time monitoring system.

*2) Real-time processing framework:* Experimental results confirm the framework's efficiency, processing 245 fault events with optimal performance ($<$1 ms processing time and $<$1 ms blockchain update time, Table VI). This capability, tested across diverse medical devices, highlights minimal latency and high reliability, surpassing conventional systems and enabling rapid fault resolution critical for patient safety.

*3) Enhanced security and traceability:* The blockchain-enabled architecture maintains complete, tamper-proof fault histories, as demonstrated by the secure block structure (Fig. 3) and SHA-256 hash implementation (Table III). This ensures regulatory compliance and data integrity, with the system achieving 100% message delivery reliability, addressing healthcare's stringent security demands.

*4) Intelligent fault diagnostics:* LLM integration enhances diagnostic precision, with models like O3-mini achieving 90.4% diagnosis accuracy and 91.2% core problem identification (Table VII). Comparative analysis (Fig. 7) reveals superior fault differentiation over traditional ML (73.6% diagnosis accuracy), providing actionable insights for proactive maintenance and advancing diagnostic depth in healthcare settings.

*5) Healthcare-specific implementation:* The framework's scalability and compliance are proven through its modular six-layer architecture (Fig. 1) and practical deployment across multiple device types (Table IV). Processing efficiency (e.g., Traditional ML at 10.68 cases/minute, Fig. 9) and offline capabilities (e.g., Deepseek-R1-7B, CDE: 90.6%) ensure adaptability to healthcare standards, enhancing device reliability and patient care coordination via EHR integration.

These results collectively outperform conventional methodologies, as shown in the comparative analysis of AI models (Table VII), with O3-mini (CDE: 93.6%) and Deepseek-R1-7B (CDE: 90.6%) leading in diagnostic effectiveness. The framework's ability to balance accuracy, efficiency, and security positions it as a transformative tool for Healthcare 4.0.

## VI. Conclusion and Future Work

This research unveils a Healthcare 4.0 framework that integrates IoT, blockchain, and LLM to advance medical device fault diagnosis, providing a secure, intelligent and efficient solution validated through extensive testing. Evaluations in ECG monitors, insulin pumps and defibrillators affirm the efficacy of the framework, achieving real-time fault detection with minimal blockchain overhead (0.1227 seconds), ensuring data immutability and secure traceability essential for compliance and patient safety. LLM outperforms ML, with O3-mini achieving 90. 4% diagnosis precision and 91. 2% identification of the core problem compared to ML's 73. 6% in both, highlighting the precision of LLM in fault analysis. In contrast, ML excels in processing efficiency at 10.68 cases per minute versus O3-mini 3.59, which suits time-sensitive needs, while offline LLM capabilities, such as the high effectiveness of Deepseek-R1-7B, enhance security in restricted settings.

These results support the study's contributions: IoT-blockchain-LLM integration enables robust real-time monitoring; the processing framework surpasses conventional systems in latency and reliability; blockchain ensures security and fault history integrity; LLM provides actionable diagnostic insights; and the scalable architecture meets healthcare standards, boosting device reliability and EHR coordination. The analysis positions O3-mini and Deepseek-R1-7B as diagnostic leaders, marking the framework as transformative for Healthcare 4.0.

Future efforts will improve the efficiency of LLM processing to match ML speed via hardware optimization or hardware,

expanding its use in real-time. Extending federated learning will enhance diagnostic accuracy across networks, while broadening device support and refining blockchain mechanisms will reduce latency. Advancing predictive maintenance through pattern analysis will take advantage of LLM strengths, and integrating with healthcare systems and improved security will ensure greater adoption and compliance. These steps will strengthen the framework's role in revolutionizing medical device management and patient safety.

The demonstrated success of this integrated approach provides a foundation for continued development in medical device fault diagnostics, potentially transforming how healthcare facilities manage and maintain critical medical equipment. This work contributes significantly to the field of Healthcare 4.0, offering a secure, intelligent, and efficient solution for medical device maintenance and monitoring.

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# Knowledge Discovery of the Internet of Things (IoT) Using Large Language Model

Bassma Saleh Alsulami
Department of Computer Science-Faculty of Computing and Information Technology,
King Abdulaziz University, Jeddah 21589, Saudi Arabia

***Abstract*—Internet of Things (IoT) technology quickly transformed traditional management and engagement techniques in several sectors. This work explores the trends and applications of the Internet of Things in industries, including agriculture, education, transportation, water management, air quality monitoring, underground mining, smart retail, smart home systems, and weather forecasting. The methodology involves a comprehensive review of the literature, followed by data extraction and analysis using BERT to identify key insights and patterns in IoT applications. The findings show that IoT significantly impacts the improvement of real-time monitoring, increasing efficiency, and encouraging innovative solutions in various sectors. Despite its transformative potential, cybersecurity threats, data privacy concerns, and the need for strong policy frameworks persist. The study emphasizes the necessity of multidisciplinary approaches to address these difficulties and optimize IoT implementation. Future research should focus on establishing secure IoT systems, maintaining data integrity, and encouraging collaboration between disciplines to realise the benefits of IoT technology.**

***Keywords*—Internet of Things; large language model; BERT; knowledge discovery; data mining; deep learning**

## I. Introduction

The Internet of Things (IoT) has appeared as a significant milestone in the digital era of intelligence and creativity that has gone beyond being just a technological innovation and has become a widespread force transforming society, industry [1], and daily life because of the increasing number of networked devices, sensors, and systems. As this study navigates the complex and interconnected world of IoT, it is crucial to thoroughly investigate its fundamental principles, applications, and substantial consequences. IoT combines electronic and analogue domains to enable convenient communication between things and machines. The IoT relies on pervasive connectivity and intelligent automation by incorporating devices, such as sensors, actuators, and networking technologies, into smartphones, wearables, household appliances, and industrial equipment to allow entities to collect, evaluate, and share data in real-time through the network. Knowledge discovery refers to systematically extracting significant patterns and insights from extensive datasets. This approach is crucial for making well-informed decisions, enhancing operations, promoting innovation, managing risks, and enabling customization. Text classification [2], [3] is closely connected to extracting and categorizing textual material into predetermined classes, a crucial aspect of extracting relevant information from text corpora.

The Internet of Things (IoT) is present in every aspect of modern life, including healthcare, manufacturing, agriculture, education, transportation [4], and urban development. IoT healthcare devices and customised and proactive healthcare allow patients to check vital signs, fitness, and chronic conditions in real-time. IoT enables intelligent industries to optimise and automate manufacturing production processes by integrating equipment, robots, and sensors. Additionally, the IoT could revolutionise agriculture. Sensor data, satellite imagery, and machine learning algorithms optimise crop yield, resource conservation, and environmental impact in precision agriculture systems. Smart vehicles and infrastructure systems enabled by IoT enable autonomous driving, intelligent traffic control, and seamless mobility, providing a safer and more efficient transportation network. IoT devices and continual connectivity generate massive amounts of data, raising privacy, security, data ownership, and compliance concerns. Furthermore, the digital divide worsens pre-existing disparities, putting marginalised areas in danger of being excluded from the advantages of IoT-driven progress. As this study explores the complexity of IoT, it becomes clear that its potential is accompanied by obstacles and intricacies. IoT ecosystems' vast size and intricate nature provide significant difficulties regarding compatibility, ability to grow, dependability, and ease of control. Moreover, there is a significant concern about cybersecurity concerns, as IoT devices are often targeted by malevolent individuals who aim to take advantage of weaknesses and damage data integrity. To overcome these obstacles, a multidisciplinary strategy is needed to traverse the changing IoT environment. This method must consider computer science, engineering, economics, sociology, ethics, and policymaking. This study can use the Internet of Things (IoT) to reshape society, innovate, and solve problems by encouraging cross-disciplinary collaboration and knowledge exchange.

This research study aims to thoroughly analyse IoT, encompassing its theoretical basis, technological framework, and societal consequences. By combining current literature, case studies, and empirical research, this study aims to shed light on the intricate and helpful aspects of the Internet of Things (IoT). This will offer valuable insights to guide future research, policy development, and technological advancements.

The rest of the paper is structured as follows: Section II reviews the existing studies and establishes the research gap. Section III discusses the proposed methodology to extract the knowledge of IoT. Section IV and V provide the result and discussion. Section VI concludes and describes the future direction.

## II. Literature Review

This section studies some research and reviews papers focusing on information retrieval or data mining approaches to discover IoT's state-of-the-art technologies and applied domains.

Naghib et al. [5] reviewed 110 articles from 2016 to 2022 related to IoT's big data management methods. They distributed the articles into four categories: architectures, processes, analytics types, and quality attributes. Sunhare et al. [6] discussed the data mining methods used in diverse IoT applications, for example, smart home, smart grid, smart agriculture, etc., and big data mining solutions, like reinforcement learning, Markov chain model, and so on. Amin et al. [7] discussed smart cities and how IoT and ML may build data-centric smart environments to improve citizen's satisfaction with technology and data. They also presented smart city functions and the challenges of adopting IoT and machine learning in cities, which can enhance urban surroundings by rendering them more livable, sustainable, and efficient. Cyberattack's growing frequency and complexity significantly threaten sensitive data, financial stability, and national security, making cybersecurity a paramount concern. Cyber-attacks have a significant impact on the IoT environment. Alqurashi and Ahmad [8] proposed a scientometric approach to discover the knowledge of cyber threats, different types of malware, malware detection techniques, etc., from cybersecurity-related research articles. Sarker et al. [9] presented IoT security methods, including machine learning and deep learning algorithms, challenges, solutions, and future directions for further study.

The process of knowledge discovery involves the analysis of a large amount of information to extract contextual information, which domain experts or knowledge-based systems can utilise to address challenges within the domain. Ahmad et al. [4] proposed a deep journalism concept by incorporating different sources, such as research articles, magazines, and newspapers, to discover the multi-perspective knowledge (i.e., academic, governance, and industrial) for transportation.

## III. Methodology and Design

### A. Dataset

We collected 28,160 research articles from the Web of Science (WoS) between 2014 and 2024. The following query is applied to find the research articles: "TS= ("internet of things") OR TS=(IoT)". Additionally, this study selected only "English" written articles, and the following filtering strategies are applied: document type (article and proceeding paper), WoS categories (telecommunication, computer science information systems, computer science artificial intelligence, and Engineer Electrical Electronic), and research areas (computer science, telecommunications, and engineering). Fig. 1 shows the dataset word count vs. the number of articles.

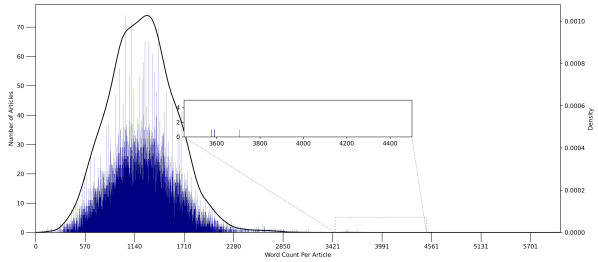


Fig. 1. Dataset word count vs. number of articles.

### B. Methodology

Fig. 2 shows the research methodology of this study. Initially, the articles collected from WoS are stored in a CSV file. After that, the following pre-processing procedures were implemented in the present research on the dataset: (1) removal of duplicate articles, (2) removing extraneous characters, (3) tokenization, (4) removal of stop words, and (5) lemmatization utilising POS tags. Subsequently, excessive articles were eliminated in the second step to reduce redundant information. In the third step, extraneous characters, such as Unicode characters, were deleted. Additionally, the texts were tokenized in the fourth stage, and stop terms were eliminated in the fifth. Clustering was initially performed using the NLTK predetermined stop word directory, followed by the execution of the BERT model. Following the generation of clusters, a keyword survey was conducted to identify superfluous keywords that exhibited significant likelihood scores. After the testing phase, a complete set of insignificant keywords was compiled for cluster generation. These keywords were incorporated into the stop-word list and extracted from the texts in the ultimate model. Finally, lemmatization was implemented using POS identifiers. The articles that were subsequently cleansed were employed for knowledge discovery.

This study used the BERTopic [10] to cluster the information and conduct knowledge extraction. At first, this study generated a grounded embedding model using BERT. This study applied the pre-trained "distilbert-base-nli-mean-tokens" method for this research because of its capacity to accomplish a satisfactory compromise between accuracy and duration of execution. This study implemented the UMAP approach, which was specifically developed to decrease the complexity of data while retaining the maximum quantity of knowledge. In addition, this study used HDBSCAN to group articles with similarities into clusters. Furthermore, a TF-IDF score that is contingent on the class is employed to ascertain the importance of terms for each cluster. TF-IDF enables the assessment of word importance in different texts by considering both the frequency of a word in a particular document and its significance in the whole collection of texts. By considering each article inside the set as a distinct unit and using TF-IDF, this study may get significant scores for the words within the cluster. The class-TF-IDF score is the numerical value that quantifies the significance of a word in a document compared to a group of documents. The cluster grows more representative as the words' relevance increases. As a consequence, this study could obtain descriptions that are derived from keywords for each measure. Once this study obtained the class-TF-IDF, continue to add all the information and train the BERT model. The class-TF-IDF determinants of the articles were adjusted to reduce the number of clusters. The cluster with the greatest frequency is then combined with the most comparable cluster, as determined by their class-TF-IDF matrices. Ultimately, this study assigned clusters to all

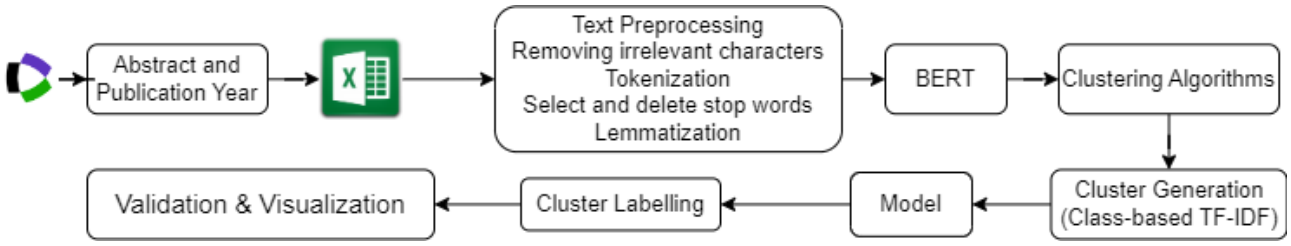


Fig. 2. Methodology.

TABLE I. CLUSTERS FOR IOT

| Clusters | No. | Keywords |
|---|---|---|
| Technology | 0 | network, device, system, application, model, sensor, technology, security, performance, design, method, wireless |
| Agriculture | 1 | agriculture, food, system, crop, soil, plant, farm, irrigation, moisture, field, disease, temperature |
| IoT Device | 2 | device, less, energy, system, battery, network, communication, frequency, voltage, node |
| Education | 3 | student, robot, education, teaching, learn, campus, course, application, university, classroom |
| Transportation | 4 | vehicle, parking, traffic, car, road, driver, accident, bus, parking lot, congestion, parking space |
| Water IoT | 5 | water, underwater, water quality, monitoring, fish, river, consumption, marine, level |
| Air IoT | 6 | air, waste, pollution, disaster, fire, garbage, evacuation, air pollution, waste management |
| Underground Mining | 7 | mine, railway, underground, gas, train, coal, oil, mining, coal mine, oil gas |
| Smart Retail | 8 | visitor, shopping, cultural, tourist, customer, RFID, store, retail, checkout, travel |
| Smart Home | 9 | sleep, wake, energy, device, mode, sleep mode, consumption, quality, network |
| Ride Sharing | 10 | bike, bicycle, cycling, bike sharing, system, station, city, crash, mountaineer, prediction, rider, team |
| Weather IoT | 11 | weather, temperature, rainfall, humidity, rain, weather parameter, collect, wind, rain value, pressure |

the articles and saved the model. This study comprehensively analysed the corresponding cluster articles since the cluster is originally represented as an integer number. Subsequently, this study labelled the clusters using specialised knowledge and quantitative analytical methods such as hierarchical clustering.

## IV. RESULT

Table I shows the research discoveries by listing the clusters with the corresponding cluster No. and keywords.

Vasco et al. [11] explore the significance of IoT technology for those with impairments, emphasising its capacity to enhance the quality of life and self-determination. This study [12] presents a novel approach for identifying potential attacks on Internet of Things devices using a game-theoretic mathematical model. The approach seeks to address efforts to compromise IoT devices, such as the Mirai botnet, which is the biggest known botnet and orchestrated an assault involving around 100,000 devices. Xie et al. [13] suggest using a knowledge graph-based multilayer IoT middleware to connect IoT devices that use multiple protocols, thereby overcoming the communication barrier between them. Utilising a graph-based knowledge system, it universally oversees all Internet of Things (IoT) devices. The technique's efficacy was shown in a project that monitored rural sewage treatment stations in China.

Smart Agriculture [14] employs automated and ICT-driven technology to tackle climate change and meet nutritional requirements. Cloud services and improved interconnectivity technologies combine and integrate the characteristics of IoT technology. Advanced interfaces are necessary for customisation and remote engagement. This study [15] suggests using Conversational User Interfaces (CUI) to control Internet of Things (IoT) devices in the field of smart agriculture. A chatbot system using natural language processing offers an effective, safe, and user-friendly platform for engaging with Internet of Things (IoT) devices specifically suited for agricultural applications. IoT technology improves the quality of education [16], [17] by offering intelligent recommender systems that enable students to choose courses and institutions depending on their educational standards. This is achieved by using fog-cloud computing to collect data on the academic environment. Sustainable traffic management is rendered possible by smart cities having well-designed smart parking systems. Appropriate parking spot tracking and control may be facilitated by integrating many enabling innovations, such as 5G connectivity, Unmanned Aerial Vehicles (UAVs), and the IoT. This [18] study suggests an intelligent parking system to monitor parking spot availability using various devices and unmanned aerial vehicles (UAVs). This improves precision and lowers the number of false positives and negatives. Water is an essential component of daily existence. Water preservation and control have become vital for human life because of the state of the environment worldwide. There has been a great demand recently for consumer-driven humanitarian initiatives that might be built quickly using IoT technologies [19].

Increasing air pollution, which affects indoor air quality and results in 1.6 million premature deaths yearly, is connected to the world's population growth. Businesses are creating inexpensive sensors with IoT applications to track interior air pollution. Communities must overcome some constraints when choosing sensors to solve this public health issue [20]. The mining sector depends on underground mining to recover rich minerals. Many sectors have used automation to improve worker security, streamline processes, boost event reaction times, and attain cost-effectiveness. An ongoing interaction and tracking framework is required to reduce serious risks and enhance security in underground mines. However, particles and hazardous, flammable, and volatile gases impact the atmosphere in underground mines. Because the hazardous gases can potentially explode, they pose a serious risk [21]. In today's world, tourism is a rapidly growing industry that generates jobs and economic growth. Travellers are using more and more technology to make the most of their trips. With the IoT facilitating information transmission and distribution,

smart tourism makes IoT technology [22] a vital element of travellers' toolkits.

Computerised checkout systems provide the potential for increased sales by enhancing the customer experience and decreasing costs through less reliance on shop staff. The current study focuses on the conceptual aspects of an automated checkout system in fashion retail businesses. Integrating a cyber-physical platform into existing retail settings is difficult due to architectural limitations, standard customer procedures, and consumer demands for confidentiality and practicality, which restrict system design options. Hauser [23] focuses on implementing a computerised checkout system in fashion retail outlets, addressing obstacles such as architectural limitations and consumer demands. The system uses an RFID device and software elements to accurately and effectively identify purchases, associating them with specific purchasing baskets. The method is deployed and assessed in a research facility, demonstrating notable precision and effectiveness, though its performance drops to 42% in demanding settings. Utilising wearable sensors for sleep monitoring provides a cost-efficient alternative to the costly polysomnography procedures used in hospitals. This research [24] employs an Internet of Things (IoT) platform and an event-driven microservice architecture to monitor ECG data daily. The prediction of weather across the majority of the globe continues to rely on statistical and computational methods. Statistical and computational analysis yields more accurate outcomes, but its effectiveness relies heavily on consistent past correlations to forecast future values. Conversely, machine learning investigates novel algorithmic methods for making predictions that rely on data-driven analysis. Several elements, such as precipitation, temperature, air pressure, moisture, wind velocity, and other variables subject to change, influence the climatic variations in a certain region. Given that specific locations influence climatic changes, traditional statistical and computational methodologies may sometimes be ineffective and require an alternative strategy, such as using machine learning to comprehend weather forecasting better. Balamurugan [25] demonstrates that conventional forecasting techniques for June 2019 produced a rainfall percentage range of 46-91%. However, predictions generated using machine learning algorithms surpassed statistical approaches in accurately predicting rainfall.

The intertopic distance is displayed in Fig. 3. The knowledge is shown as a circle in a 2D space, where the gap between any two circles reflects the degree of disparity between the knowledge. The diameter of each circle corresponds to the frequency in the dataset. Topics nearby demonstrate more resemblance or a heightened commonality regarding their subject matter or context. The x-axis of this depiction is labelled as "Topic 0" to "Topic 11," suggesting a consecutive numbering of separate subjects. Meanwhile, the y-axis is divided into two distinct dimensions, D1 and D2. This representation simplifies understanding of the data structure and uncovers relationships that are not apparent in a complex setting. For instance, the biggest circle (topic 0) denotes a salient topic in the dataset, and its proximity to another circle suggests a significant link between the two topics. The arrangement of smaller circles on the map signifies a spectrum of less prevalent, distinct subjects within the dataset.

Fig. 4 shows a sequence of horizontal bar graphs, where

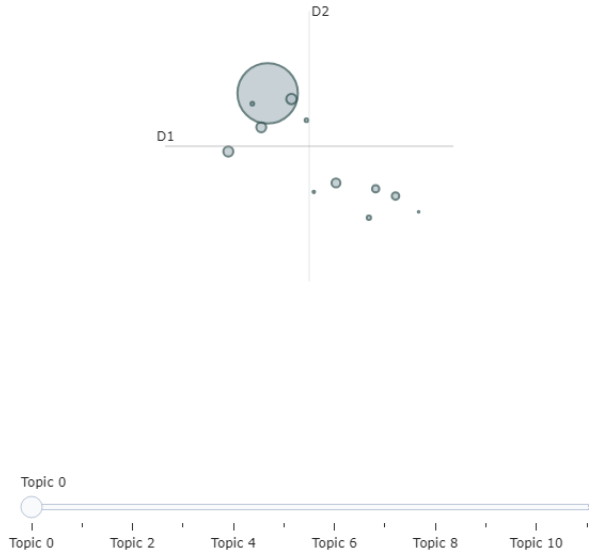


Fig. 3. Intertopic distance.

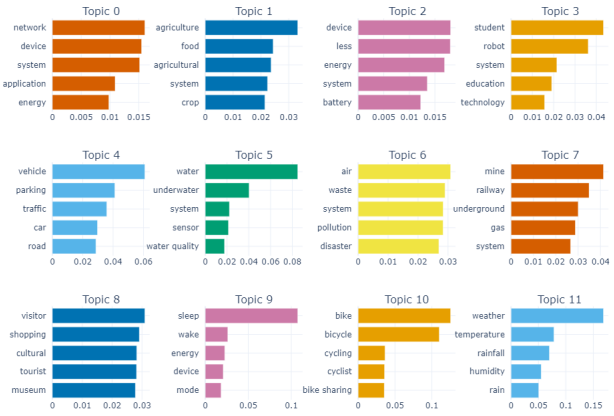


Fig. 4. Top 5 words for each cluster.

each graph corresponds to a separate cluster or topic. Each bar's size correlates to a word's significance within its respective topic. The subject areas are classified by colour and include a diverse range of subjects, such as technology, agriculture IoT, IoT devices, education IoT, transportation IoT, water IoT, air IoT, underground mining, smart retail, smart home, ride-sharing, and weather in Topics 0 to 11, respectively. Topic 4 is notable for its focus on the transportation aspects of IoT, demonstrated by the following keywords: "vehicle", "parking", and "traffic". The visualisation enables easy recognition of the most prominent words in all topics, which is essential for understanding the major themes of a large amount of text and for summing up the information within each resultant topic. Furthermore, this study uses a class-dependent TF-IDF score to determine the importance of terms for each cluster. TF-IDF enables the assessment of word importance in different texts by considering both the frequency of a word in a particular document and its significance in the whole collection of documents.

Fig. 5 depicts a dendrogram that is the outcome of a hierarchical cluster analysis. The horizontal axis depicts the

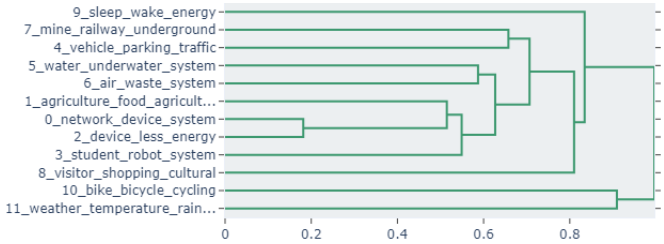


Fig. 5. Hierarchical cluster.

disparity between groups, with a smaller distance indicating a greater similarity. It is evident that some clusters exhibit a tight grouping, such as the cluster "0-network-device-ssystem" with the cluster "2-device-less-energy.s" This indicates the presence of closely associated topics within the data.

## V. Discussion

This research examines the diverse range of industries in which IoT technology is being used, such as agriculture [26], education, transportation, water management, air quality monitoring, underground mining, smart retail, smart home systems, ride-sharing services, and weather forecasting. This study investigation revealed the widespread impact of IoT devices in transforming conventional procedures and improving efficiency and production in various areas. IoT solutions in agriculture provide immediate monitoring of environmental conditions, soil moisture levels, and crop health, allowing for precise farming methods and efficient use of resources. Similarly, in the field of education, smart classrooms equipped with IoT technology provide interactive learning experiences and personalised instructional techniques. Transportation Internet of Things (IoT) applications optimise logistical operations, increase fleet management, and improve passenger experiences using real-time traffic monitoring and predictive repair. Water Internet of Things (IoT) technologies aid in the sustainable management of resources by monitoring water quality, identifying leaks, and optimising irrigation techniques. Airborne Internet of Things (IoT) devices serve a crucial role in monitoring and assessing the levels of air pollution, ensuring the general population's protection and well-being. IoT-enabled safety monitoring, asset tracking, and predictive maintenance in underground mining operations enhance worker safety and operational efficiency. In addition, IoT technologies are transforming retail experiences by providing personalised purchasing suggestions, optimising inventory management, and improving consumer interaction. Smart houses utilise Internet of Things (IoT) devices to automate household duties, improve security measures, and optimise energy usage. Ride-sharing services use the Internet of Things (IoT) to optimise routes, estimate demand, and enhance passenger safety. In addition, weather forecasting technologies provided by the Internet of Things (IoT) offer precise and fast information for preparing for disasters and allocating resources. The extensive use of IoT technology in many industries highlights its significant capacity to shape the future of linked systems and services.

The benefits of IoT devices include enhanced efficiency, productivity, and security in various applications. However, the research's comprehensive scope may overlook technological complexities, cybersecurity threats, economic obstacles, and interoperability challenges. Additionally, the study lacks detailed discussions on regulatory and ethical considerations and the dependence on stable internet connectivity. Addressing these challenges is crucial for fully harnessing the potential of IoT, providing a balanced view of the future of connected systems and services.

## VI. Conclusion

This study provides a comprehensive analysis of the influence of IoT technology in many sectors, such as agriculture and transportation. The statement emphasizes the ability of the Internet of Things to facilitate immediate monitoring, enhance effectiveness, and stimulate innovation. In the future, it is important to prioritize conducting additional research to improve cybersecurity measures and reinforce data privacy rules to reduce the dangers and weaknesses inherent in IoT systems. Furthermore, it is imperative to guarantee the authenticity and dependability of data within IoT frameworks and address concerns regarding data's precision and credibility. To optimize the societal advantages of the IoT, fostering interdisciplinary collaboration and forging collaborations across many industries is crucial. Researchers can accelerate the progress of IoT technology by concentrating on these specific areas. This will involve tackling the obstacles associated with IoT and promoting its incorporation into many sectors and fields.

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# Rib Bone Extraction Towards Liver Isolating in CT Scans Using Active Contour Segmentation Methods

Mahmoud S. Jawarneh[1], Shahid Munir Shah[2],
Mahmoud M. Aljawarneh[3], Ra'ed M. Al-Khatib[4], Mahmood G. Al-Bashayreh[5]
Faculty of Information Technology Applied Science Private University Amman, Jordan 11937[1,3,5]
Faculty of Eng. Sciences and Technology, Hamdard University, Karachi, Pakistan 74600[2]
Department of Computer Sciences, Yarmouk University, Irbid, Jordan 21163[4]

***Abstract*—Image segmentation is an important aspect of image processing and analysis. Medical imaging segmentation is critical for providing noninvasive information about human body structure that helps physicians analyze body anatomies efficiently. Until recently, various medical imaging segmentation approaches have been presented; however, these approaches are deficient in segmenting abdominal organs due to the significant similarity in their intensity levels. The purpose of this research is to propose a method to facilitate the segmentation of abdominal organs and improve the performance of the segmentation. The core functionality of this research is based on the extraction of rib bone from muscle tissues prior to the application of segmentation. This way, efficient segmentation of abdominal organs can be achieved by isolating the rib bone from the muscle tissues located between the rib bone. The proposed rib bone extraction mechanism is applied to four slices of the MICCAI2007 liver data set to isolate muscle tissues from liver tissues that have significant intensity similarity to liver tissues. The results indicate that the proposed extraction of rib bone efficiently isolated muscle tissues from linked liver tissues and improved the segmentation performance.**

***Keywords*—Active contour; computed tomography; segmentation; medical diagnostics; medical imaging segmentation**

## I. Introduction

Image segmentation aims to partition an image into regions called segments used for further image analysis to achieve improved image compression efficiency and visualization effects [1], [2]. Image segmentation plays a vital role in medical imaging analysis for example providing noninvasive information about human body structure [3]. This information can support radiologists in visualizing and examining the anatomy of the body structure [4], tracking the progress of diseases [5], [6], [7], simulating biological processes [8], and evaluating the need for surgeries in radiotherapy [9], [10]. Threshold-based, region-growth-based, clustering-based, deformation-model based, machine learning (ML)-based, and active contour-based are different segmentation approaches that have been frequently employed in medical imaging analysis [11]. Medical imaging segmentation is important, yet it is a challenging task.

Most of the time, it requires manual delineation of organs by highly skilled personnel. Segmenting CT images is particularly complex compared to other medical imaging modalities. In such images, selecting each pixel of each slice manually could take hours or even days [12], [13]. Segmenting CT images of abdominal organs is more challenging because of their overlapping boundaries with the other organs (such as abdominal structure tissues and muscle tissues placed between rib bone). Most of the abdominal organs have similar intensity levels, which greatly affects the segmentation results of the methods based on intensity similarity [14]. Hence, methods based on gradient or intensity analysis are not feasible to segment images of abdominal organs [15]. Because of such limitations, most available segmentation methods, including active contour methods, fail to segment the abdominal tissues adjacent to the muscle tissues between rib bone [16], [17], [18]. Specific to the active contour segmentation methods, some existing approaches [19], [20], [21] adapted rib distance in the active contour level set formulation. This process slows the active contour segmentation since the contour curve takes longer to reach structural boundaries due to extra computations in the level set function.

Keeping in view the limitations of the existing studies, the following are the research questions that may be addressed during this research:

- How existing segmentation methods based on the intensity of the organs can segment the abdominal organs having similar intensity?
- How the efficiency of the existing segmentation method based on the intensity of the organs can be increased?

Extracting rib bone structures prior to applying the active contour method may facilitate the removal of intervening muscle tissues, thereby improving segmentation efficiency. The primary purpose of this research is to propose a method to facilitate the segmentation of abdominal organs with considerable similarity in intensity by performing rib bone extraction prior to active contour segmentation methods. The following are the objectives of the research:

- To improve the segmentation accuracy of the abdominal organs affected by the large similarity in intensity between abdominal structure tissues and muscle tissues located in between rib bone.
- To reduce the computation time while segmenting abdominal organs via active contour segmentation methods in the CT dataset. As a result, this leads to speeding up the processing time.

Based on the listed objectives, following are the contributions of the research:

- A rib bone extraction mechanism is proposed to efficiently segment the CT images of abdominal organs of similar intensity.
- The proposed rib bone extraction isolates the rib bone from the muscle tissues located in between the rib bone.
- The proposed rib bone extraction is specifically designed to be used prior to the application of "active contour" segmentation methods and has tested accordingly; however, it may be used prior to the application of any segmentation method.
- The proposed rib bone extraction has been applied to four MICCAI2007 Liver dataset [22], [23] slices to efficiently isolate liver tissues from muscle tissues with similar intensities.
- The proposed rib bone extraction simplifies the CT images and addresses the similarity of their intensity issue; hence, leads to a time and computationally efficient segmentation.
- The proposed approach is simple and easy to use, as well as applied prior to the application of the segmentation method(s). To the best of our knowledge, such an approach has never been proposed earlier, hence making it our novel contribution.

Based on the above listed research contributions, the following may be the advantages of the present study:

- The findings of the research will help clinicians efficiently segment, analyze, and visualize abdominal anatomies, as well as plan radiation therapy and surgery.
- The study's research findings will be used to assist software designers in constructing medical tools.
- The approach proposed in this study will help in teaching and research at medical schools.
- The methodologies and results proposed in this study will be useful in medical schools, teaching, and research.

The remainder of the paper is organized as follows: Section "Literature Review" explores and discusses reviewed literature in the area of medical imaging segmentation. Section "Material and Method" discusses the detailed methodology of the proposed method of extracting muscle tissues using the proposed rib bone extraction method before executing the active contour segmentation. "Results and Discussion" section discusses the results of the proposed method. Finally, "Conclusion and Future Direction" section presents the conclusion of the paper to highlight the contributions and findings along with possible future directions. A preprint of this manuscript has previously been published [24].

## II. Related Work

Medical imaging segmentation has been a research focus from last few decades. During this time, a number of image segmentation techniques have been put forth to segment medical imaging for a range of applications, including the early diagnosis of disease, resource optimization, and maximizing efficiency of the existing systems etc. Image segmentation techniques include but not limited to; thresholding based [25], [26], [27], region growing based [28], [29], graph cut based [30], [31], shape model based [32], [33], edge detection based [34], [35], [36], clustering based [37], [38], [39], and more advanced ML [40], [41], [42], [43], and active contour-based methods [44], [45], [46]. In addition to significant contributions to image segmentation, particularly medical imaging segmentation, each proposed approach pose some limitations and challenges. For example, thresholding and region growing based methods are bound to use only image intensity or texture for the image segmentation [47], therefore, are failed to segment the organs with similar intensities. Graph-cut based methods are also limited in segmenting organs with overlapping tissues of similar intensities [31]. Shape based methods are heavily dependent on the training shapes, therefore, become time consuming processes for the images with large shape variations [48]. Recently, ML algorithms (specifically, Deep Learning (DL) algorithms), have emerged as efficient approaches for segmenting medical images [49], [50]. However, DL techniques frequently lack in understanding data and heavily rely on training data that has been manually labeled by medical professionals [48]. Furthermore, because of information loss in the consecutive down-sampling layers, some DL architectures, such as Convolutions Neural Network (CNN), perform poorly in comprehending precise object boundaries [51]. Also, in CNN architectures, 2D convolutions cannot completely utilize the spatial information along the third dimension [52], and 3D convolutions have a large memory consumption [53]. DL-based multi-organ segmentation techniques have also shown significant potential in medical imaging segmentation [54], and it has significantly improved the performance of the U-NET segmentation [55], however it is still challenging to obtain accurate and robust segmentation for the areas with ambiguous boundaries (such as abdominal organs) [56].

Supervised Machine Learning models such as Support Vector Machines (SVM) and Neural Networks (NN) have also shown reasonable performance in segmenting medical images, however, these methods are based on handcrafted and manually extracted features from the data, and for this heavily depend on the skills and experience of the researchers. Requirements of domain knowledge, extraction of features from data, and manual features engineering is basic hurdle to easily employ such algorithms [57], [49]. Active contour methods on the other hand have shown better performance to segment the complex gray-scale and variety of topological structures of medical images [58]. Because of their ability to provide closed and smooth contours of the target objects, these methods are one of the widely used segmentation methods today [59]. Many recent studies have reported to use active contour methods for different applications related to medical imaging segmentation [60], [61], [62], [63]. Although, active contour segmentation is one of the most attractive segmentations, however, in some cases it performs undesirably. For example, it performs poorly in segmenting complex natural images (without proper preprocessing) [64]. Furthermore, because of the susceptibility for intensity heterogeneity and boundary ambiguity of the input images, these methods fail to segment the abdominal tissues, especially tissues, which are adjacent to the muscle tissues between rib bone [65].

To address such limitation of the active contour methods, as a solution, combination of different strategies along with traditional active contour methods have been introduced by the researchers. For example, level set approach has been introduced with active contour to formulate it as energy minimization problem and then solving it with different strategies like gradient descent or partial differential equations [66]. Different DL architectures like CNN have also been combined with active contour to make it a more efficient hybrid segmentation methods [67]. Some of the studies have also introduced the combination of DL, level set, and active contours methods [68]. Such hybrid methodologies yielded good results but suffer with the time consumption issues because of the complexity of the training process. In short, introducing different strategies with traditional active contour methods, one way increases their segmentation capabilities, but on the other hand make them time consuming procedures. Furthermore, even with the latest proposed strategies, still the most existing active contour segmentation methods lack in segmenting the overlapping organs / region boundaries of the organs [69], [70], [71]. This study proposes that rib bone extraction be performed prior to active contour segmentation (refer to "Methodology" section for more information on the proposed method). The proposed approach is an effort to improve the accuracy of the active contour method(s) in particular and the other segmentation methods in general to segment abdominal organs (especially abdominal structure tissues and muscle tissues placed between rib bone) that have comparable intensity levels. Being not the actual part of the active contour, the proposed approach reduces the computation time of the active contour while segmenting abdominal organs. As a result, this leads to speeding up the processing time. Results show that with the help of the proposed approach, the active contour better segments abdominal organs (refer to Fig. 2) and achieves desirable performance in segmenting the organs of the similar intensity (refer to Section "Results and Discussion" for more details on the results achieved). The next section provides the comprehensive detail of the proposed rib bone extraction mechanisms along with the detail of the datasets used, experimentation performed, and the results obtained.

## III. Material and Method

### A. Proposed Approach

This study proposes that rib bone extraction be performed prior to active contour segmentation. This approach can be used to improve the accuracy of the active contour segmentation in particular and the other segmentation approaches in general in segmenting abdominal organs that have comparable intensity levels (i.e., abdominal structure tissues and muscle tissues placed between rib bone).

### B. Methodology

Fig. 1 presents the overall flow diagram of the proposed rib bone extraction approach. According to Fig. 1, the proposed strategy of rib bone extraction is achieved through the following steps:

1) Typical slice of a CT image selection.
2) Performing thresholding on the selected typical slice to find rib bone in it.
3) Performing morphological post processing on the thresholded typical slice to eliminate the effects of thresholding on it.
4) Finding the centroids of each rib bone of the typical slice and saving them as cooperative knowledge for the other slices of the data.
5) Selecting the next slice (target slice) and finding the centroids of its rib bone using the centroid information of the typical slice.
6) Fitting the centroids of typical and target slices into convex hull function (to overcome the problem of the missing centroids).

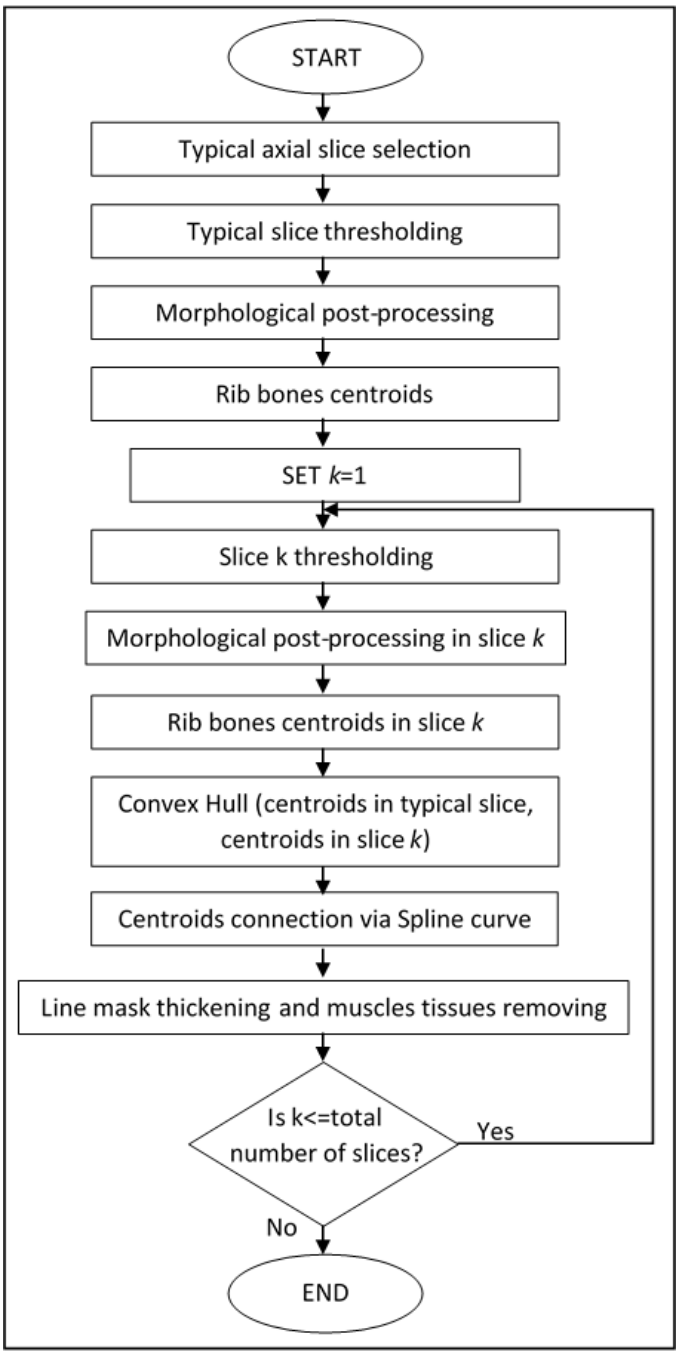



Fig. 1. Proposed rib bones extraction approach.

7) Applying the spline curve method to connect the centroids and estimating the bone's boundary by a line.
8) Applying dilation morphological operation to thicken the estimated lined boundary.
9) Applying steps 5 to 8 above to every next slice by considering it a target slice until the slices of the whole data are finished.

An explanation of each of the above steps is provided in detail in the experimentation subsection.

### C. Performance Evaluation

*1) Evaluation based on Confusion Matrix:* Performances of the proposed system has been measured in terms of accuracy, precision, sensitivity, and specificity provided using the confusion matrix. Table I presents the confusion matrix used to compute the performance measures. The outcomes of this confusion matrix are defined as:

True Positive (TP): The number of slices where muscles areas are removed as muscles areas.

False Positive (FP): The number of slices in which non-muscles areas are removed as muscles areas.

True Negative (TN): The number of slices where non-muscles areas are not removed as muscles areas.

False Negative (FN): The number of slices where muscles areas are not removed as muscles areas.

TABLE I. CONFUSION MATRIX FOR MUSCLE AREA CLASSIFICATION

| | Yes | No |
|---|---|---|
| **MUSCLES AREA** | TP | FN |
| **NON-MUSCLES AREA** | FP | TN |

The confusion matrix presented in Table I and four standard metrics for quantities evaluations are computed as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

*2) Evaluation based on 2D segmentation:* In order to evaluate the proposed method, the method outputs need to be measured, analyzed and compared with manual segmentation. Therefore, the metrics must be carefully determined to accurately reflect the method performance in 2D segmentation performance. Dice coefficient (mean Index similarity) used to measure the accuracy of segmentation result for proposed method. The segmentation result of proposed method is termed AS and the gold standard is termed GT. The Dice coefficient DC (Dice, 1945) is one of the numbers of measures of the extent of spatial overlap between two segmented images. It is commonly used in reporting performance of segmentation and its values range between 0 if there is no overlap between the segmented region and the gold standard, and 1 for perfect agreement between the segmented region and the gold standard obtained using Eq. (5).

$$\text{DC} = \frac{2\,|AS \cap GT|}{|AS| + |GT|} \tag{5}$$

### D. Experimentation

*1) Dataset description:* The proposed method was evaluated using four contrast-enhanced CT datasets from the Liver Segmentation Grand Challenge database. These datasets have a pixel resolution ranging from 0.55 mm to 0.8 mm, with inter-slice distances between 1 mm and 3 mm. Each axial slice consists of 512 x 512 pixels. The datasets, provided in Digital Imaging and Communications in Medicine (DICOM) format, have gray levels ranging from -1024 to +3071, corresponding to Hounsfield units (HU), the datasets accessed in 2024. The datasets used in this study—Liver1, Liver3, Liver4, and Liver6—contain 183, 79, 212, and 111 slices, respectively. However, the range of liver organ slice in each dataset shown in Table II.

TABLE II. ABDOMINAL ORGANS DATASETS

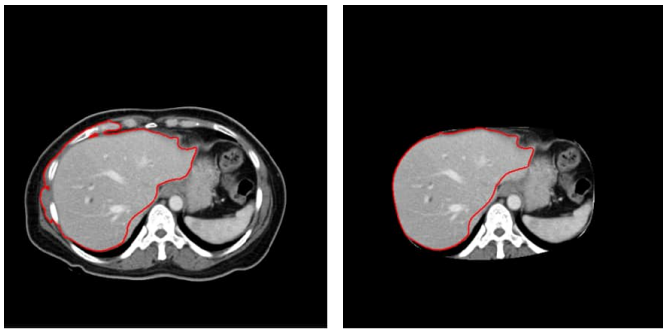
| Abdominal Dataset Name | Dataset Source | Number of Slices | Range of Abdominal Organs Slices |
|---|---|---|---|
| Liver1 | MICCAI2007 | 183 | 62–163 |
| Liver3 | MICCAI2007 | 79 | 14–70 |
| Liver4 | MICCAI2007 | 212 | 57–196 |
| Liver6 | MICCAI2007 | 111 | 20–92 |

*2) Software detail:* Image segmentation and statistical calculations are implemented in Matlab. The program is tested on a computer with Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz 2.71 GHz, 4GB RAM, and Windows 10 Pro.

*3) Rib bone extraction process:* This section provides the detail of the proposed rib bone extraction approach along with the brief explanation of each step provided in the "proposed approach" subsection, and also shown the Fig. 1.

Fig. 2(a) illustrates the results of active contour segmentation before rib bone and muscle extraction, and Fig. 2(b) shows the result of active contour segmentation after rib bone and muscle extraction. It is clear from Fig. 2(a) and 2(b) that when rib bone extraction is performed prior to active contour segmentation, active contour segments the organs of similar intensity, i.e., abdominal organs, comparatively better than when rib bone extraction is not performed. This approach is the main idea our research.

It is well-known among radiology experts that some abdominal structures, especially the liver, are surrounded by rib bone. Therefore, their effective segmentation is difficult without rib bone extraction from their surroundings. Since the rib bone has the highest intensity in a CT dataset, simple binary thresholding may be applied to find the rib bone in it. In binary thresholding, images are converted from gray-scale or color images to binary images. Based on radiologists' knowledge, it is noted that there are some slices that don't have rib bone in all directions of the human body in the abdominal area, which leads to missing some of the muscle tissues. The proposed method thus finds the rib bone in a



(a) Before bone extraction. (b) After bone extraction.

Fig. 2. Active contour segmentation before and after rib bone and muscle extraction from the abdominal organs of similar intensity.

typical slice chosen randomly from upper abdominal slices in the CT dataset, which have rib bone in all directions, as shown in Fig. 3, and applies binary thresholding on the chosen slice. Fig. 4(a) shows a typical slice in the upper abdominal region (upper view) and the result of thresholding in a typical slice shown in Fig. 4(b).

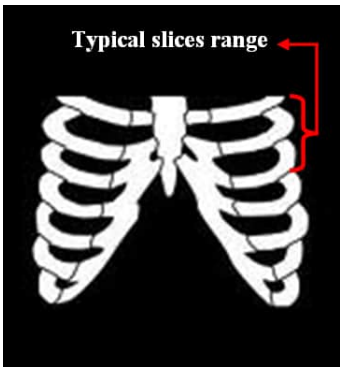
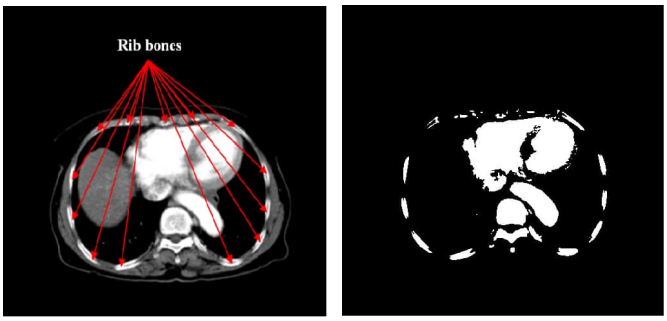



Fig. 3. A Typical slice chosen from the upper abdominal CT slices that have rib bones in all directions.

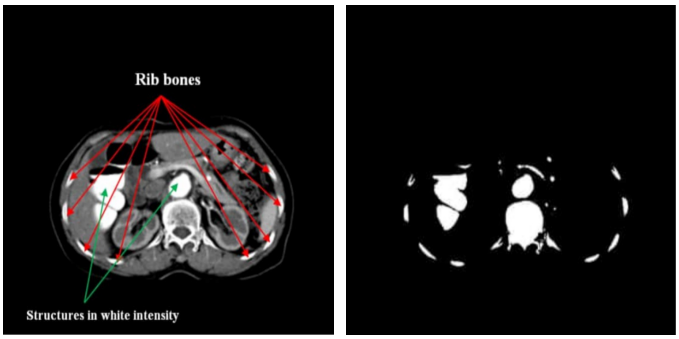



(a) Upper view of a typical slice in the upper abdominal region that has rib bones in all directions. (b) Upper view of the rib bone extraction after thresholding applied

Fig. 4. Typical slice.

It is evident from Fig 4(b) that, as a result of thresholding, the achieved rib bone is not well filled. Hence, a filling morphological operation is applied to fill the bone. The centroids of each rib are then computed. The centroids of ribs of the typical slice are saved temporarily to be used as a cooperative knowledge in the rib bone extraction for other remaining slices in the dataset. The rib bone extraction process is then applied to all slices in the abdominal dataset slice by slice with the following steps: To simplify the explanation, we refer to the slice under the rib bone extraction process as a target slice. Thresholding and filling morphological operations are applied to the target slice. The centroids of each rib bone in the target slice are obtained through region properties. Then the centroids of the typical slice and target slice are fitted into the convex hull function [72].

This function is used to find the appropriate arrangement in a clockwise cycle for these bones' centroids and take just the outer centroids. In some cases, some abdominal structures appear in white intensity, as shown in Fig. 5(a), which can affect the result of extracting ribs and muscles. However, the convex hull process overcomes those obstacles. In addition, the convex hull process also overcomes the problem of missing centroids in some directions by taking the centroids from a typical slice in the same directions. Fig. 5(a) shows an example of a target slice that does not have rib bones in all directions, and its thresholding result is shown in Fig. 5(b).




(a) Ribs in target slice. (b) Thresholding result.

Fig. 5. Target slice and its resultant slice after the application of thresholding.

The convex hull process is followed by the spline curve method to connect the centroids and estimate the bone's boundary. The connected points are then used to form a mask that isolates muscle tissues. Fig. 6 shows the line connecting the rib bones. The line connecting between the rib bones is then thickened by a dilation morphological operation (as shown in Fig. 7). The formed mask is applied to remove muscles located between rib bones.

This operation aims to remove the rib bones and muscles, which solve the problem of intensity similarity with abdominal structure tissues. Fig. 8 shows removing ribs and muscles. Choosing an appropriate thickening for connecting line is an essential factor that affects the accuracy of segmentation results. We choose an appropriate thickening value through experiments. Fig. 9 shows the effect of line mask thickening size; if the mask line thickened uses a bigger value, the mask will isolate some of the abdominal structure tissues, as shown in Fig. 9(b). If the mask line thickened to an appropriate size, the mask will isolate rib bones and muscles tissue only, as shown in Fig. 9(a).

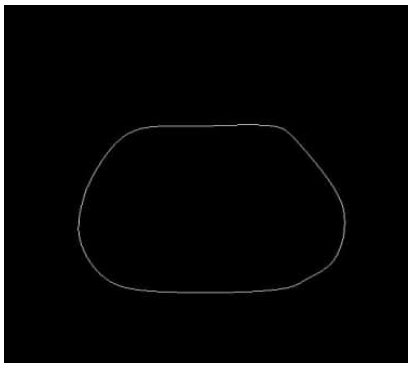


Fig. 6. Line connected between ribs.

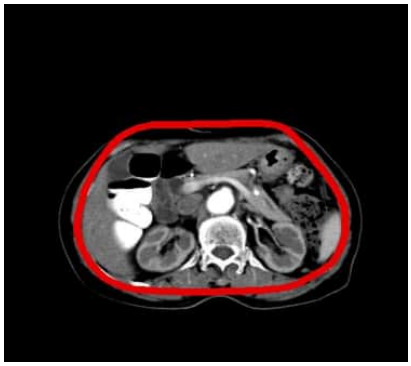


Fig. 7. Line thickening by the application of dilation morphological operation.

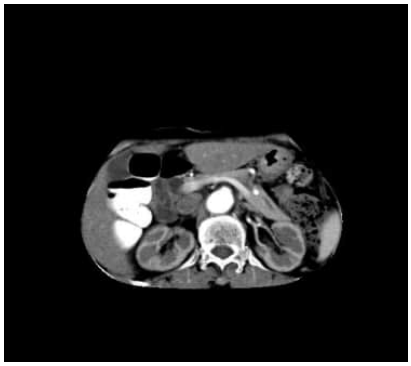
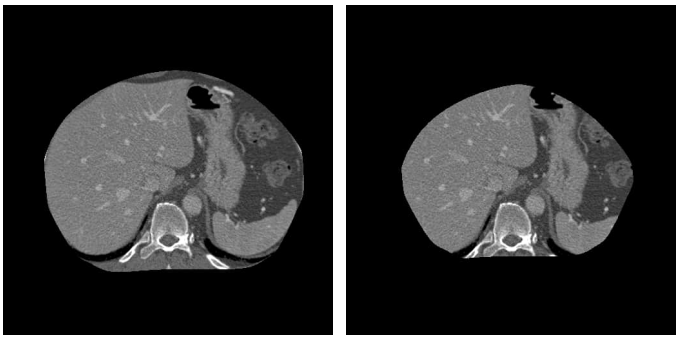


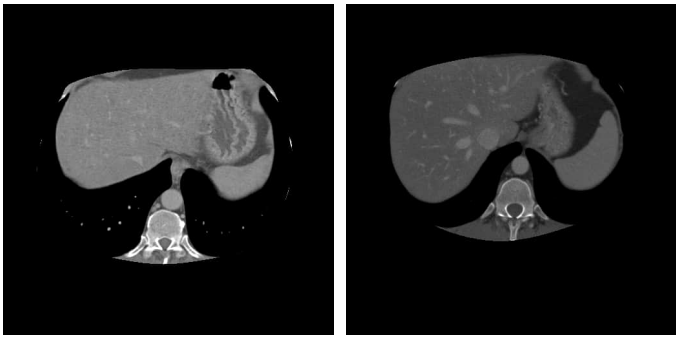
Fig. 8. Removal of rib bones from muscles.



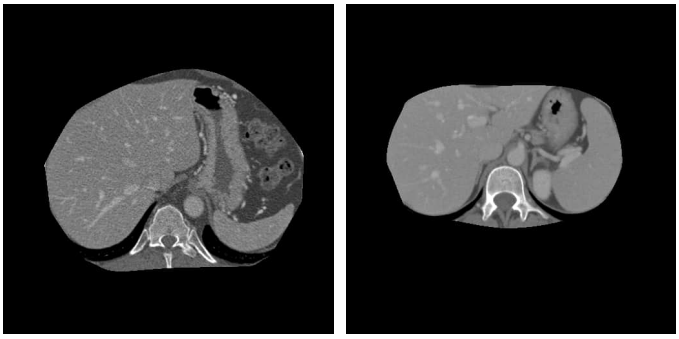
(a) Appropriate thickening. (b) Big thickening.

Fig. 9. Effects of line thickening on rib bone and muscles separation.

Rib bones extraction is applied to four MICCAI2007 Liver datasets [22], [23] (liver1, liver3, liver4, and liver6) slices to isolate muscle tissues that have significant intensity similarity with liver tissues. Fig. 10 shows rib bone extraction for some slices in these datasets [i.e. Fig. 10(a) (slice 151 Liver1), Fig. 10(b) (slice 61 Liver3), Fig. 10(c) (slice 158 Liver4), and Fig. 10(d) (slice 64 Liver6)]. Rib bones extraction is not performed on the Liver5 dataset due to the clear distinction in intensity between the liver tissue and muscles tissue.



(a) Slice 151 Liver1 (b) Slice 61 Liver3



(c) Slice 158 Liver4 (d) Slice 64 Liver6

Fig. 10. Rib bones extraction applied to four MICCAI2007 Liver datasets i.e. liver1, liver3, liver4, and liver6.

## IV. Results and Discussion

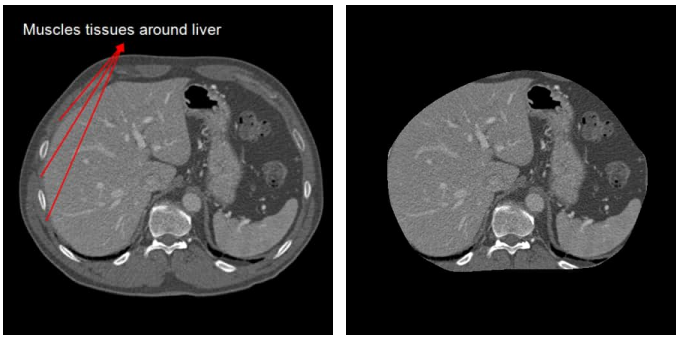
### A. Results Based on Confusion Matrix

Table III shows the evaluations quantities for each Liver data set and the weighted average performance where the weights correspond to the number of slices in each dataset. Results presented in Table III indicates that the proposed approach has efficiently extracted the rib bones from the slices of the Liver dataset.

TABLE III. Quantitative Evaluations for Rib Bone Extraction

| Dataset | Slices Number | Accuracy | Precision | Sensitivity | Specificity |
|---|---|---|---|---|---|
| liver1 | 102 | 0.83 | 0.80 | 0.96 | 0.78 |
| liver3 | 57 | 0.86 | 0.82 | 0.93 | 0.79 |
| liver4 | 140 | 0.92 | 0.88 | 0.96 | 0.87 |
| liver6 | 73 | 0.84 | 0.92 | 0.75 | 0.93 |
| **Average** | - | 0.87 | 0.86 | 0.91 | 0.84 |

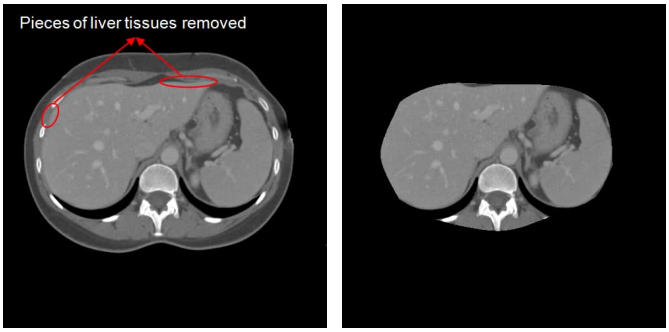
Fig. 11 [Fig. 11(a) (original slice), and Fig. 11(b) (muscles isolating)] shows an example of a true positive (TP) case where the muscle tissue between rib bones is isolated completely.




(a) Original slice (b) Muscles isolating

Fig. 11. A true positive case where the muscle tissue between rib bones is isolated completely from muscles.

Fig. 12 [Fig. 12(a) (original slice), and Fig. 12(b) (pieces removed)] shows an example of a false positive (FP) case where some parts of liver tissues (non-muscle tissues) are removed as a muscle area. From rib bone extraction results, it can be noted that the efficiency of this method is acceptable.




(a) Original slice (b) Pieces removed

Fig. 12. A false positive case where some parts of liver tissues are removed as muscle.

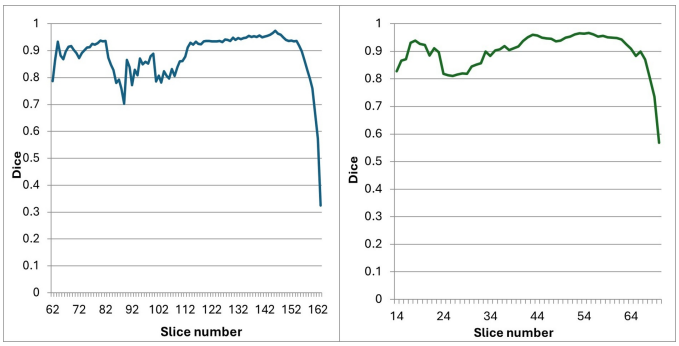
### B. Results Based on Dice Coefficient

Table IV shows the mean Dice coefficient values in all datasets, all slices for each liver organ. Fig. 13 (a)–(d) show the results of the Dice coefficient for the liver regions in the four MICCAI2007 liver datasets (Liver1, Liver3, Liver4 and Liver6).

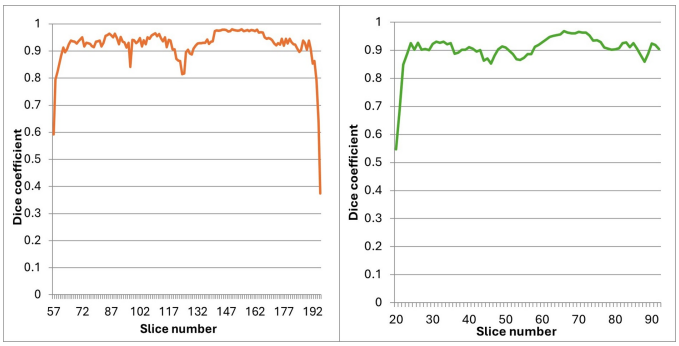
TABLE IV. QUANTITATIVE MEASURES FOR FOUR LIVER ORGAN DATASETS

| Dataset | Number of Segmented Liver Slices | Mean Dice Coefficient |
|---|---|---|
| Liver1 | 102 | 0.88 |
| Liver3 | 57 | 0.90 |
| Liver4 | 140 | 0.92 |
| Liver6 | 73 | 0.90 |
| **Average** | – | 0.90 |

The quantitative measures presented in Fig. 13 and Table IV, shows a positive correlation and high similarity between the proposed method and the experts' manual segmentation, reflected by the mean of Dice coefficient for all four liver organs (0.90).




(a) Liver1 (b) Liver3




(c) Liver4 (d) Liver6

Fig. 13. Dice coefficient for four liver organs: Proposed method versus manual segmentation.

Finally, the results achieved in this study are compared with the state of-the-art active contour-based segmentation methods in the literature i.e. [71], [73]. As Compared to [71], [73] our proposed model achieved promising results in terms of precision, recall, and f-measures scores.

## V. CONCLUSION AND FUTURE DIRECTIONS

In this research, a rib bone extraction mechanism is proposed to be used prior to segmentation methods such as active contour to segment abdominal organs of similar intensity. Similar intensity of abdominal organs, such as abdominal structure tissues and muscle tissues located in between rib bone, greatly affects the performance of the segmentation methods, and most available segmentation approaches based on intensity of the organs, fail to efficiently segment these organs. The proposed rib bone extraction is used to isolate muscle tissues that have similar intensity with abdominal structure tissues; hence, it makes the segmentation process computationally efficient and simpler to use. The rib bone extraction mechanism isolates muscle tissues with a large degree of similarity in their intensity with the abdominal structure. Consequently, this prevents the active contour curve from leaking into muscle tissues during the segmentation process. The proposed rib bone extraction is applied on four MICCAI2007 Liver data set [22], [23] slices to isolate muscle tissues from liver tissues that have significant similarity in intensity with liver tissues. Results indicate that the proposed rib bone extraction approach has efficiently isolated muscle tissues from the linked liver tissues.

The proposed rib bone extraction is specifically designed

to be used prior to the application of "active contour" segmentation methods and has been tested accordingly; however, it may be used prior to the application of any segmentation method.

In future, this method will be tested with the other state-of-the-art segmentation approaches to check its suitability with these methods and to better validate our hypothesis.

## Data Availability

MICCAI2007 data were used to support this study and are available at https://www.semanticscholar.org/paper/Semi-automatic-Segmentation-of-the-Liver-and-its-onDawantLi/bacf1b9ffec68f01d93d6389faea03432060e07d. These prior studies (and datasets) are cited at relevant places within the text as reference [22], [23].

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# Revolutionizing Road Safety and Optimization with AI: Insights from Enterprise Implementation

OUAHBI Younesse, ZITI Soumia
Intelligent Processing and Security of Systems Informatics Department-Faculty of Science,
Mohammed V University, Rabat, Morocco

***Abstract*—This study explores the key factors influencing the adoption of artificial intelligence (AI) in the logistics sector, with a particular emphasis on road logistics management. It examines the technological, organizational, and environmental contexts that shape AI integration, as well as the challenges faced by logistics managers, including the need for digital transformation, carbon emissions reduction, and advanced parcel tracking management. The objective is to identify technological and human-related barriers to AI adoption and to assess the level of interest and readiness among logistics companies, especially in the Moroccan context. A quantitative research approach was adopted, based on an online survey targeting logistics professionals and decision-makers, mainly from European and Moroccan small and medium-sized enterprises (SMEs). The collected data were analyzed using statistical methods, including linear regression and ANOVA, to evaluate the relationships between company characteristics, perceived complexity of AI tools, and the availability of qualified human resources. The findings indicate that perceived complexity and limited access to specialized skills significantly hinder AI adoption. Moreover, the perception of tangible performance benefits—such as increased operational efficiency and reduced $CO_2$ emissions—emerges as a major driver for acceptance. These insights offer practical implications for logistics companies seeking to leverage AI technologies to optimize operations, reduce environmental impact, and enhance parcel tracking systems. A strategic roadmap is proposed to overcome the identified barriers and promote effective AI integration.**

***Keywords*—AI adoption; road logistics; logistics management; digital transformation; $CO_2$ emissions; parcel tracking management**

## I. Introduction

The logistics sector is a fundamental pillar of the global economy, ensuring the smooth functioning of supply chains and the fluidity of international trade [1]. However, the logistics sector faces major challenges that impact not only its operational efficiency but also its sustainability and safety [2]. Three key issues stand out: road accidents [3], CO2 emissions [4], and parcel tracking management [5]. These concerns are critical for logistics companies and have significant global repercussions on society and the environment. According to the latest report from the World Health Organization (WHO), the number of people killed in road accidents amounts to 1.19 million per year [6]. Although this figure represents a slight decrease, road accidents remain the leading cause of death among children and young people aged 5 to 29, with more than two deaths per minute and over 3,200 per day. The WHO's 2023 Global Road Safety Status Report indicates that between 2010 and 2023, the number of road accident fatalities decreased by 5%. Despite this reduction, road accidents continue to represent a global health crisis, with pedestrians, cyclists, and other vulnerable road users remaining particularly at risk [6].

In 2022, according to statistics reported by the National Road Safety Agency (NARSA), Morocco recorded 113,625 traffic-related injuries, resulting in the deaths of 3,499 people. Among these victims, more than 1,600 people lost their lives on non-urban roads (1,629). Approximately six-sevenths of the fatalities were men (2,971), while around one-seventh were women (515). A total of 889 victims were under the age of 25, including 281 under the age of 15, and 608 aged 15 to 24. Of The victims included 1,398 users of motorized two or three-wheelers (1,321 two-wheelers and 77 three-wheelers). Pedestrians accounted for 888 of the victims, representing 25.4% of the deaths, with just over one-fifth (189) of them aged 65 or older. Additionally, 801 victims were users of passenger cars [7]. Enhancing road safety by preventing collision accidents is a key objective within the transportation system, driving the advancement of collision prevention technologies. By leveraging detection, computer, and communication technologies, the main goal of these systems is to accurately identify potential driving hazards. They can then either warn the driver or automatically apply braking at the right moment, thereby reducing the risk of accidents [8]. CO2 emissions generated by transport vehicles pose a significant environmental challenge [9-12]. Logistics vehicles, including trucks, vans, and utility vehicles, are responsible for a substantial share of global greenhouse gas emissions [4],[13-15]. According to the 2023 report by the International Energy Agency (IEA), the transport sector accounts for approximately 24% of global energy-related CO2 emissions, with heavy-duty trucks contributing nearly 30% of these emissions. In 2022, heavy trucks were responsible for 7.3% of total CO2 emissions in the European Union, with similar figures observed in other regions of the world. The need to reduce the carbon footprint has become a major imperative, not only to meet increasingly stringent environmental regulations but also to satisfy the growing consumer expectations for sustainability [15]. Logistics companies face the challenge of balancing operational efficiency with emission reductions [10]. Solutions such as route optimization, smart driving technologies, and the transition to greener vehicles are crucial for achieving these goals. However, the implementation of these solutions requires significant investments and substantial operational adjustments, which can be a major obstacle for many companies [11]. Artificial Intelligence (AI) offers transformative solutions to the major challenges in the logistics sec- tor, particularly in addressing road accidents, CO2 emissions, and parcel tracking management. By leveraging advanced algorithms and data processing technologies, AI enables significant improvements

in logistics operations while contributing to a substantial reduction in associated risks and costs [12–14].

In terms of road accident prevention, AI plays a crucial role through the use of safety management systems based on predictive analytics. These systems integrate data from sensors, cameras, and driving history to detect risky behaviors and hazardous conditions. For instance, AI algorithms can analyze driving habits and weather conditions to anticipate accident risks and recommend preventive measures [8]. Regarding route optimization, AI provides significant solutions for reducing CO2 emissions. Dynamic routing algorithms enable real-time adjustments to routes based on traffic conditions, thereby minimizing fuel consumption and greenhouse gas emissions. According to the International Energy Agency, this optimization could reduce CO2 emissions in the transport sector by 10% to 15% by 2030 [15]. Additionally, an analysis by McKinsey & Company suggests that adopting AI technologies for route optimization could result in fuel savings of up to 20% [16]. In terms of parcel tracking, AI enhances accuracy and transparency through technologies like smart sensors and data management systems. By enabling real-time tracking, AI reduces errors and delays while increasing customer satisfaction. A study by Capgemini [17] revealed that AI solutions could improve delivery forecast accuracy by 30% and decrease order processing errors by 25%. Additionally, AI provides greater transparency for customers, thereby strengthening their trust and loyalty [17].

AI also plays a significant role in human resource management within the logistics sector. AI tools can monitor driver attendance, analyze their performance, and predict human resource needs, thereby optimizing resource management and productivity. A study by Deloitte shows that AI can improve operational efficiency by 15% to 20%, reducing labor costs and increasing employee productivity [18], [1]. The adoption of AI in road logistics in Morocco is still in the development phase. Although AI offers significant opportunities to optimize logistics operations, its integration faces several major challenges. Key obstacles include technological complexity, the high cost of solutions, and issues related to user training [19]. This study aims to analyze the factors influencing the adoption of AI in logistics, identify the problems encoun- tered by logistics managers, and understand how technological, organizational, and environmental contexts affect the integration of this technology.

While previous studies focused on individual components of AI deployment in logistics, few have addressed enterprise-level AI adoption combining both safety and optimization. This paper seeks to fill this gap and it's the primary objectives of this study also to identify the technological barriers to AI adoption. This includes challenges related to training AI systems, associated costs, and the perceived complexity of AI tools. Another objective is to identify specific issues in road logistics that could be addressed by AI. This analysis aims to shed light on common challenges such as vehicle tracking, fuel consumption management, and vehicle condition monitoring. It is also crucial to assess the need and interest of Moroccan companies in AI solutions for logistics management. This evaluation will help determine the interest in AI technologies and the willingness to invest in these solutions. Finally, the study proposes to formulate innovative solutions to improve logistics management using AI, aiming to optimize operations, prevent common issues, and enhance safety. The central research questions include:

- What are the main technological obstacles encountered when adopting AI in logistics?
- What specific problems in road logistics could be resolved by AI?
- How do organizational and environmental contexts influence the integration of AI in logistics?

The remainder of this paper is structured as follows: Section II reviews related works on AI in logistics; Section III presents the methodology and dataset; Section IV discusses the implementation and results; finally, Section V concludes the paper and suggests future work.

## II. Related Work

The application of artificial intelligence (AI) to road safety and logistics optimization has attracted considerable scholarly interest. Numerous studies have proposed and implemented AI-based techniques—including neural networks, fuzzy logic systems, ensemble learning, and conditional random fields (CRFs)—to address key challenges such as accident prediction, driver behavior analysis, and last-mile delivery optimization. To improve clarity and coherence, we have structured the literature review around four key technological approaches, each summarized in a dedicated comparison table. These tables group together relevant studies based on their primary methodological focus and application domain:

- Table I covers optimization strategies in AGV operations and real-time accident prediction.
- Table II summarizes behavior recognition and sequence modeling using CRFs and decision systems.
- Table III details the studies on accident prediction using neural networks and machine learning techniques.
- Table IV highlight the studies on driving behaviour analysis and accident prediction using fuzzy logic (2024–2025).

### A. Genetic Algorithms

Genetic algorithms, inspired by Darwin's evolutionary theory, are heuristic-based search methods that use operations like mutation and crossover to optimize solutions [20]. These algorithms start with a group of potential solutions, known as a population, which are usually represented as one-dimensional arrays. The initial population is generated randomly according to the rules defined by the problem domain. Successive generations are then created by selecting the most effective solutions from the current population [21]. The effectiveness of each candidate solution is assessed using a fitness function, with the goal of improving the performance of the new population over the previous one. Solutions with higher fitness are more likely to be selected for reproduction, where crossover and mutation are applied to create new generations of candidates [22][23] (see Table I).

TABLE I. SUMMARY OF STUDIES ON OPTIMIZATION TECHNIQUES IN AGV OPERATIONS AND ACCIDENT PREDICTION (UPDATED 2022–2025)

| Study | Objective | Method | Results |
|---|---|---|---|
| Patidar et al. (2025) [54] | Explore novel optimization algorithms for predictive modeling | Implementation of Royal Animal Optimization with hybrid approaches | Improved predictive accuracy compared to conventional models |
| Dakic et al. (2024) [55] | Optimize intrusion detection in autonomous vehicle environments | Use of metaheuristic algorithms for IoT/IIoT-based security enhancement | Achieved superior detection rates in simulated autonomous driving scenarios |
| Kumari & Mishra (2024) [56] | Enhance predictive stacking models using Bayesian optimization | Data sampling, gradient boosting, and optimization using Bayesian techniques | Enhanced performance and generalization ability for time-sensitive predictions |
| Ashraf et al. (2024) [57] | AI-based decision system for optimizing road safety | Hybrid decision-making approach with aggregation operators and multi-criteria evaluation | Enabled faster and more accurate decision-making under complex road scenarios |
| Haseena et al. (2022) [58] | Early prediction of road-related heart disease using bio-inspired models | Moth-Flame Optimization algorithm combined with deep feature extraction | Significantly improved early detection capability for accident-related health deterioration |

### B. Autonomous Driving Technology

An autonomous vehicle is a sophisticated system that can navigate and understand its environment using onboard sensors. It can autonomously plan routes and make driving decisions [24]. The Society of Automotive Engineers (SAE) defines autonomous driving across six levels in its 2014 standard, updated in 2018. Levels 0 to 3 describe a gradual shift from complete human control to partial oversight and assistance. Levels 4 and 5 indicate a stage where human intervention is no longer necessary. Modern autonomous driving systems incorporate various technologies, focusing on vehicle perception, decision-making, and control to take over driving tasks. These vehicles also utilize communication technology to stay connected with other vehicles and their surroundings, ensuring ongoing network interaction [25].

### C. Conditional Random Fields

Conditional Random Fields (CRFs) are probabilistic graphical models used for tasks such as labeling and segmenting sequential data [26]. Unlike traditional classifiers that predict labels for individual samples independently, CRFs consider the full sequence of observations when making predictions [27]. CRFs oper- ate using an undirected graph, which avoids biases related to the number of states. These models are trained in a discriminative manner and combine features of both discriminative and generative approaches, leveraging the Markov property in hidden states for observations [28]. Due to the temporal correlations present in multi-channel sequential data, traditional discriminative classifiers are not directly applicable. CRFs have been employed as an alternative inference model for this purpose [26]. This makes CRFs particularly useful for tasks that require structured prediction within sequences where maintaining temporal dependencies is essential [27] (see Table II)

### D. Artificial Neural Networks

Artificial neural networks are advanced statistical tools designed to capture intricate relationships be- tween inputs and outputs and to identify data patterns [29]. They offer a valuable alternative for exploring nonlinear dynamics in engineering contexts. The development of an artificial neural network involves three key stages: design, training, and evaluation. The design stage includes defining the rules, setting input parameters, and gathering data [31] . During the training stage, the network is refined by preparing data and adjusting learning algorithms[32] . The final evaluation stage assesses the network's accuracy and performance by comparing predicted outputs with actual results [33] (see Table III).

### E. Fuzzy Logic

Fuzzy logic represents decisions in a way that mimics natural language rather than relying solely on numerical values. Unlike traditional approaches that use numbers, fuzzy logic allows decisions to be articulated in terms of descriptive words, mirroring human-like reasoning processes [37][38][56]. This approach enables machines to simulate human thought processes more effectively. A key element of fuzzy logic is the fuzzy inference system, which can model complex, nonlinear functions through the use of fuzzy rules and convert vector inputs into scalar outputs with ease [40]. The system consists of four primary components: the fuzzifier, the inference engine, the rule base, and the defuzzifier. The fuzzifier translates inputs into fuzzy membership values, while the rule base consists of rules formulated by experts [41], [60], [61] (see Table IV).

## III. METHODOLOGY

### A. Development of Hypotheses

The development of hypotheses is a crucial step in structuring the study, allowing for the formulation of conjectures based on preliminary observations and theoretical knowledge. In the context of the adoption of AI technologies in the logistics sector, four main hypotheses have been defined to guide the analysis and evaluate the factors influencing this adoption.

- Hypothesis 1: Only companies with large logistics systems are interested in integrating AI into their operations.

The first hypothesis posits that only companies with large logistics systems are interested in integrat- ing AI into their operations. This hypothesis is based on the idea that large companies, due to the complexity and scale of their logistics systems, may see significant benefits in implementing AI solutions to optimize their processes. Large companies, with their specific needs and financial capacity, are likely to invest more in advanced technologies to improve operational efficiency and manage complex supply chains [42]. This hypothesis is grounded in the Resource-Based View theory. According to this theory, large companies possess superior resources and capabilities that enable them to invest in advanced technologies such as AI. These resources include not only financial aspects but also organizational skills and infrastructure necessary to integrate new technologies. The RBV suggests that companies with more resources are better positioned to adopt technological innovations, like AI, to maintain a competitive advantage [43, 44]. Therefore, we examine how large companies, compared to small and medium-sized enterprises, are more likely to

TABLE II. STUDIES ON THE USE OF CONDITIONAL RANDOM FIELDS FOR DANGEROUS DRIVING DETECTION AND PREDICTION

| Study | Objective | Method | Results |
|---|---|---|---|
| Chen et al. (2025) [59] | Identify major depressive disorder in elderly using behavioral markers | Behavioral feature extraction from passive data and statistical modeling | Enabled early detection through analysis of driving-related mental health indicators |
| Ortigoso-Narro et al. (2025) [60] | Propose a lightweight attention network for behavior recognition | Spatially-focused attention L-SFAN model trained on mobility data | Achieved real-time inference for driver-related pattern recognition tasks |
| Mehta et al. (2025) [61] | Predict customer satisfaction using driving and marketing behavior data | Multi-source data fusion and AI-powered behavioral analytics | Demonstrated behavioral prediction performance applicable to logistics and delivery |
| Duan (2024) [62] | Analyze behavior of tourism consumers under driving scenarios | Deep learning-based modeling of driving and consumer interaction patterns | Identified influencing factors in behavioral tourism and mobility context |
| Wang et al. (2024) [63] | Predict couriers' behavior during last-mile delivery operations | Reinforcement learning model applied to courier decision sequences | Accurate prediction of delivery performance and behavior in urban logistics |

adopt and implement AI solutions due to their more abundant resources.

To explore this hypothesis, we examined several variables related to the size and age of the company. Variable SI 5, which asks how many years the company has been in operation, allows us to assess the company's age, a factor that may influence its ability to adopt new technologies. Variable SI 6, regarding the number of employees, is also crucial for understanding the size of the company and its available resources. Larger or older companies may have more resources to invest in AI and manage its complex demands. These variables help determine how the size and length of operation of the company influence its approach to adopting AI.

- Hypothesis 2: Perceived complexity of AI tools slows their adoption in logistics.

The second hypothesis suggests that the perceived complexity of AI tools slows their adoption in the logistics sector. This hypothesis is based on the Technology Acceptance Model (TAM), which indicates that the perception of the difficulty of using a technology can be a major barrier to its adoption. AI tools, often considered technically sophisticated, may be perceived as intimidating or difficult to integrate into existing systems, potentially hindering their adoption by companies hesitant to face these challenges [45]. This hypothesis mobilizes the Technology Acceptance Model. TAM proposes that two main factors influence technology acceptance: perceived ease of use and perceived usefulness. The perceived complexity of AI may increase the perceived difficulty of use, which could discourage its adoption. According to TAM, the more a technology is perceived as complex, the less likely it is to be adopted [46]. We test this hypothesis by exploring how the perception of the complexity of AI tools affects their acceptance in the logistics sector. This hypothesis is tested using variables that measure the perception of complexity and associated costs of using AI tools. Variables TA 1 and TA 2, which concern the time and cost of training for AI systems, are essential for assessing whether perceived obstacles related to complexity influence adoption. Variable TA 12 directly measures the perception of AI technology complexity, while TA 9 evaluates the ease of use of AI tools within the company. These combined variables allow us to analyze how perceptions of complexity and costs affect the decision to adopt AI technologies.

- Hypothesis 3: Companies show higher acceptance of AI solutions when they perceive direct and tangible benefits in terms of performance improvement.

The third hypothesis proposes that companies show higher acceptance of AI solutions when they perceive direct and tangible benefits in terms of performance improvement. This hypothesis is based on the idea that business decision-makers are more likely to adopt innovative technologies if these offer clear and measurable benefits, such as cost reduction, improved processing speed, or increased accuracy in logistics operations. The perception of a positive return on investment plays a crucial role in the decision to adopt new technologies [47].

This hypothesis is supported by the Diffusion of Innovations Theory. According to this theory, in- dividuals or organizations adopt innovations when they perceive significant advantages, such as performance gains, cost reduction, or quality improvement. In the context of AI, perceived benefits like process optimization and better decision-making are crucial factors for its acceptance. We explore how perceptions of potential ben- efits influence the adoption of AI technologies in the logistics sector, examining the links between perceived advantages and adoption rates [48].

For this hypothesis, the variables focus on the benefits companies expect to gain from AI. Questions SAAI 1 to SAAI 6 measure the different types of real-time visibility and detailed statistics that companies wish to obtain using AI. For example, SAAI 1 explores the desire for real-time visibility on fuel consump- tion, while SAAI 5 examines interest in detailed visibility on delivery times. These variables help understand how perceived benefits, such as improved tracking and resource management, influence the acceptance of AI technologies.

- Hypothesis 4: The Acceptance of AI solutions is positively influenced by the availability of qualified human resources for implementation.

Finally, the fourth hypothesis states that the acceptance of AI solutions is positively influenced by the availability of qualified human resources for their implementation. This hypothesis is based on the fact that the effective adoption of AI technologies requires specialized technical skills. Companies with qualified and experienced personnel are more likely to embrace these technologies because they have the capability to overcome the technical challenges associated with their implementation. The availability and expertise of staff can thus

TABLE III. STUDIES ON ACCIDENT PREDICTION USING NEURAL NETWORKS AND MACHINE LEARNING TECHNIQUES

| Study | Methodology | Results |
|---|---|---|
| Tambouratzis et al. (2010) [30] | Probabilistic Neural Network (PNN) and Decision Tree | The combined methodology improves accuracy in predicting the severity of accidents (light, serious, fatal). |
| Akin and Akbas (2010) [31] | Supervised and Unsupervised Techniques using ANN, SVM, Decision Tree | Various techniques implemented for accident prediction, combining artificial neural networks, support vector machines, and decision trees. |
| Yuejing et al. (2010) [28] | Various Techniques using ANN | Artificial neural networks used for accident prediction. |
| Moghaddam et al. (2010) [32] | Various Techniques including ANN | Artificial neural networks applied in conjunction with other methods for accident prediction. |
| Qu et al. (2012) [33] | Various Techniques including ANN | Artificial neural networks used within a multi-method approach for accident prediction. |
| Lin (2018) [34] | Proposes LSTM and CNN to predict human vehicle trajectory, combining image data for increased accuracy | Effectiveness of LSTM and CNN models in trajectory prediction. |
| Zyner et al. (2018) [35] | Uses RNN to predict driver intention at unsignaled intersections with Lidar tracking data | Effectiveness of the RNN algorithm in predicting driver intentions. |
| Mort et al. (2016) [36] | Develops a car tracking model using RNN to predict vehicle acceleration on the highway | Effectiveness of RNNs in predicting vehicle acceleration on the highway. |
| Phillips et al. (2017) [37] | Uses RNN to predict driver behavior at intersections of different shapes | Effectiveness of RNNs in predicting driver behavior at intersections. |

TABLE IV. STUDIES ON DRIVING BEHAVIOR ANALYSIS AND ACCIDENT PREDICTION USING FUZZY LOGIC (2024–2025)

| Study | Objective | Method | Results |
|---|---|---|---|
| Ennab & Mcheick (2025) [39] | Enhance explainability in AI-based safety diagnostics | Hybrid fuzzy system integrated with interpretable AI modules | Improved transparency in safety-critical environments and decision support |
| Dağkurs & Atacak (2025) [38] | Predict driving anomalies in autonomous vehicles | Ensemble method with deep and fuzzy feature integration | Detected complex risk factors and non-linear behavior in autonomous driving |
| Erdagli et al. (2024) [40] | Evaluate cardiovascular risk linked to road stress events | Fuzzy inference applied to perfusion imaging with AI classifiers | Early identification of heart stress patterns related to logistics driving strain |
| Akinsehinde et al. (2025) [41] | Achieve robust environmental prediction under uncertainty | Neuro-fuzzy model combined with time-series for rainfall prediction | Demonstrated fuzzy learning robustness under highly volatile conditions |
| Chen et al. (2025) [42] | Detect cognitive behavior under driving-related conditions | Behaviorally-derived fuzzy decision system trained on passive data | Enabled early detection of cognitive anomalies in elder drivers |

be a determining factor in the decision to adopt AI solutions [49].

This hypothesis relies on the Organizational Capability Theory. This theory posits that the availability of specific skills and expertise within an organization is essential for the successful implementation of advanced technologies. In other words, companies with qualified personnel in AI are more likely to adopt these technolo- gies. We analyze how the availability of qualified and experienced human resources influences the adoption of AI solutions in the logistics sector, emphasizing the crucial role of technical skills in the successful integration of AI technologies [50].

To evaluate this hypothesis, we analyzed variables related to the support and skills available for using AI tools. Variable TA 4 examines the availability of ongoing support from trainers or AI experts after initial training, which is essential for the successful integration of these technologies. Additionally, TA 13 measures the level of external assistance required to use AI tools, indicating the perceived competence of employees in using these technologies. These variables help assess how the availability of skills and support influences the adoption of AI technologies [51].

### B. Field Study on Implementation Probability

The methodology used to conduct the empirical study is outlined below [52][53]. In line with the goal of increasing the likelihood of AI solution implementation in the logistics sector, a quantita- tive study was conducted using an online survey. This survey targeted practitioners and decision-makers from businesses of various sizes, primarily within European SMEs, to gather relevant information on their level of interest and the factors influencing AI adoption. The online survey was chosen for its ability to reach a wide range of companies in a very short period, while allowing for anonymous and honest responses through a structured questionnaire. The study design was carefully oriented to link theoretical analyses with real-world problems encountered in the industry, thus providing a concrete context for evaluating AI technology adoption. The collected data were analyzed using appropriate statistical methods to identify trends, relationships, and key factors influencing the likelihood of AI implementation in logistics environments.

### C. Study Design

The study design was carefully crafted to ensure a thorough analysis of the factors influencing the adoption of AI technologies in logistics systems. The first step involved defining the relevant variables for the study. Among these variables, four main ones were identified as crucial: satisfaction with internal information (SII), level of innovation (LI), rate of adoption (RA) of AI technologies, and availability of qualified human resources (QHR). Each variable was meticulously selected to reflect the essential aspects of AI adoption, allowing for a comprehensive understanding of the factors at play Table V.

Once the variables were defined, the sample selection was carried out to ensure the representativeness of the results. The sample was chosen based on specific criteria, including the participants' roles in logistics and their potential exposure to AI technologies. This selection process allowed for targeting.

Once the variables were defined, the sample selection was carried out to ensure the representativeness of the results. The

sample was chosen based on specific criteria, including the participants' roles in logistics and their potential exposure to AI technologies. This selection process allowed for targeting Individuals with direct knowledge of logistics processes and the challenges associated with integrating AI ensure relevant and reliable data. The creation of the questionnaire was a key step in data collection. A structured questionnaire was developed to measure the variables of interest. The questions were designed to accurately assess participants' satisfaction with internal information, their perception of the level of innovation in their logistics systems, their rate of adoption of AI technologies, and the availability of qualified human resources for the implementation of these technologies. The questionnaire was pre-tested to ensure its clarity and relevance and to guarantee that it covered all aspects necessary for a comprehensive evaluation of the study's hypotheses. Furthermore, particular attention was paid to the design of the study model to ensure the robustness of the results. The data collected from the questionnaire were analyzed using advanced statistical tools, including SPSS, to adjust the model based on the results obtained and to identify potential biases.

### D. Model Adjustment and Survey Bias

For model adjustment and identification of potential biases in the survey, statistical analysis was con- ducted using SPSS 26.0. This process began with a linear regression analysis aimed at evaluating the relation- ship between key variables such as satisfaction with internal information (SAII), level of innovation (NI), rate of adoption of AI technologies (TA), and availability of qualified human resources (RHQ). The linear regres- sion analysis identified significant predictors of the adoption rate of AI solutions, quantifying the impact of each independent variable on the dependent variable (TA). The main goal of this analysis was to understand how these variables interact to influence companies' propensity to integrate AI solutions into their logistics processes.

Subsequently, an analysis of variance (ANOVA) was performed to explore significant differences in TA scores across different industry sectors. This statistical method identified whether certain industries are more inclined than others to adopt AI technologies based on their sectoral characteristics. ANOVA provided valuable insights into the disparities between sectors, allowing for a better understanding of the dynamics specific to each industry.

To deepen the analysis, post-hoc tests were conducted following the ANOVA to precisely identify significant differences between sectoral groups. These tests were crucial in clarifying which sectors exhibited distinct behaviors in terms of AI technology adoption.

Furthermore, special attention was given to identifying and correcting potential biases in the survey. Selection biases, non-response biases, and information biases were carefully examined to ensure the validity of the conclusions drawn from the study. Selection biases were assessed to verify if the chosen sample was representative of the target population, while non-response biases were analyzed to understand the impact of any data collection gaps. Additionally, information biases, related to how data was collected or interpreted, were considered to avoid distortions in the analysis of the results.

### E. Validation and Analysis of the Study

To validate the study, several rigorous methodological steps were followed. First, the research hypotheses were subjected to appropriate statistical tests. Categorical relationships were tested using Chi-square tests, which measure significant links between discrete variables. Simultaneously, regressions were used to analyze continuous relationships between variables, providing an in-depth understanding of the dynamics underlying the adoption of AI technologies. Next, a detailed analysis of the results was conducted to interpret the relationships between variables, identifying the factors that most influence AI adoption in different logistical contexts. This analysis revealed key trends and correlations, offering valuable insights for businesses considering implementing these technologies. Finally, particular attention was given to evaluating potential biases in the collected data. These biases were identified and accounted for to minimize their impact on the conclusions and ensure the robustness and reliability of the final study results.

## IV. Result and Discussion

The integration of Artificial Intelligence (AI) in road logistics has gained significant attention due to its potential to enhance efficiency, reduce operational costs, and improve sustainability. This section presents key findings from the study, including the demographic and professional profiles of respondents, followed by statistical analyses that examine the factors influencing AI adoption. By utilizing descriptive statistics, linear regression, and ANOVA, this research provides a comprehensive understanding of how industry-specific challenges, company characteristics, and technological factors impact the acceptance and implementation of AI solutions in logistics. The discussion highlights critical insights drawn from the data, emphasizing the practical implications for businesses seeking to integrate AI-driven innovations (see Table VI and VII).

### A. Respondent Profile

Descriptive statistics provide a detailed overview of the characteristics of the study participants. The variables analyzed include Gender, City, Current Position, Industry, Years of Company Existence, and Number of Employees. The results for these variables are summarized in Table VIII and IX.

*1) Sex:* The distribution of genders among the respondents reveals that the "Female" category is predominant, with 193 participants, representing 54.99% of the total sample. In contrast, men constitute 45.01% of the sample, with 158 participants. This over-representation of women might reflect a trend in the studied sectors or the nature of the survey respondents. It would be relevant to examine whether this distribution is representative of the target population or if it suggests a potential bias in the recruitment of participants.

*2) City:* Regarding the geographic distribution, Casablanca emerges as the most represented city, with 108 respondents, accounting for 30.77% of the sample. Tangier follows closely with 105 participants (29.91%), while Rabat and Paris have 84 (23.93%) and 34 (9.69%) participants, respectively. Other cities such as Safi and Fez have a much less significant presence, with only 2.28% and 3.42% of the respondents,

respectively. This geographic distribution indicates a concentration of respondents in the major economic cities of the country, which could influence the results based on economic characteristics and regional practices.

*3) Current positions:* The analysis of current positions reveals that the "Purchasing Manager" category is the most frequently observed, with 68 participants, representing 19.37% of the sample. The positions of "Logistics Manager" and "Supply Chain Agent" follow, with respective proportions of 16.52% and 16.81%. These key roles in management and the supply chain appear to be dominant, which may reflect their importance in the represented sectors. Less common positions, such as "SAP Consultant" and "Delivery Specialist," account for less than 2% of respondents each. This distribution of positions may indicate a concentration of expertise in certain specific areas and suggests notable specialization among the participants.

TABLE VIII. FREQUENCY TABLE FOR GENDER, CITY, CURRENT POSITION, INDUSTRY, COMPANY YEAR OF EXISTENCE, AND NUMBER OF EMPLOYEES

| Variable | n | % |
|---|---|---|
| **Gender** | | |
| Homme | 158 | 45.01 |
| Femme | 193 | 54.99 |
| Missing | 0 | 0.00 |
| **City** | | |
| Casablanca | 108 | 30.77 |
| Safi | 8 | 2.28 |
| Paris | 34 | 9.69 |
| Tanger | 105 | 29.91 |
| Fes | 12 | 3.42 |
| Rabat | 84 | 23.93 |
| Missing | 0 | 0.00 |
| **Current Position** | | |
| PDG | 18 | 5.13 |
| Gestionnaire Supply Chain | 56 | 15.95 |
| Gestionnaire Logistique | 58 | 16.52 |

*4) Industry:* Regarding the industry, the sector "National and International Transport & Transit" stands out with 90 participants (25.64%), making it the most represented sector. The "Automotive" and "Food Industry" sectors follow, with 16.52% and 15.10% of respondents, respectively. Other sectors such as "IT" and "Construction" are less represented, each accounting for less than 2% of the responses. This sectorial distribution highlights the predominance of certain economic sectors in the sample, which could influence the results based on the specific characteristics of each industry.

*5) Years of existence of the companies:* Regarding the years of existence of the companies, the majority of respondents have been in operation for over 15 years, representing 66.67% (234 participants). Companies with 10 to 15 years of existence account for 25.07% (88 participants), while those with less than 10 years of existence represent only 8.26% (29 par- ticipants). This predominance of long-established companies may reflect increased stability and experience, which are important in the context of the management practices and strategies examined in the study.

TABLE IX. FREQUENCY TABLE FOR GENDER, CITY, CURRENT POSITION, INDUSTRY, COMPANY YEAR OF EXISTENCE, AND NUMBER OF EMPLOYEES

| Variable | n | % |
|---|---|---|
| **Current Position (continued)** | | |
| Consultant SAP | 6 | 1.71 |
| Agent Supply Chain | 59 | 16.81 |
| Gestionnaire Achat | 68 | 19.37 |
| Delivery Specialist | 8 | 2.28 |
| HR | 8 | 2.28 |
| QSE et Amélioration Continue | 14 | 3.99 |
| Consultant | 21 | 5.98 |
| Agent Achat | 18 | 5.13 |
| Agent Logistique | 17 | 4.84 |
| Missing | 0 | 0.00 |
| **Industry** | | |
| IT | 8 | 2.28 |
| Services Numériques et Consulting | 11 | 3.13 |
| Aéronautique | 18 | 5.13 |
| Construction | 6 | 1.71 |
| Transport National et International and Transit | 90 | 25.64 |
| Industrie de Luxe | 21 | 5.98 |
| Automobile | 58 | 16.52 |
| Industrie Agroalimentaire | 53 | 15.10 |
| Télécommunication | 6 | 1.71 |
| Gestion de la Relation Client | 34 | 9.69 |
| Textile | 6 | 1.71 |
| Produit Pharmaceutique | 21 | 5.98 |
| Industrie de la Pêche | 19 | 5.41 |
| Missing | 0 | 0.00 |
| **Company Year of Existence** | | |
| $<$ 10 years | 29 | 8.26 |
| 10 - 15 years | 88 | 25.07 |
| 15+ years | 234 | 66.67 |
| Missing | 0 | 0.00 |
| **Number of Employees** | | |
| $<$ 10 | 29 | 8.26 |
| 10 - 50 | 88 | 25.07 |
| 51 - 500 | 202 | 57.55 |
| 500+ | 32 | 9.12 |
| Missing | 0 | 0.00 |

*6) Number of employees:* Regarding the number of employees, the "51-500" category is the most frequent, with 202 participants, accounting for 57.55% of the sample. Companies with between 10 and 50 employees represent 25.07%, while those with fewer than 10 employees and more than 500 employees have much lower representations, at 8.26% and 9.12% respectively. This distribution suggests a concentration in medium-sized companies, which could have implications for the resources available and the observed organizational practices. In conclusion, the descriptive results highlight key trends in the sample composition, including a predominance of women, a concentration in major cities, a dominance of positions related to management and supply chain, and a strong presence of established and medium-sized companies. These demographic and professional characteristics could influence perceptions and practices in the studied areas and should be considered when interpreting the survey results.

*7) Linear regression analysis:* A linear regression analysis was conducted to evaluate whether the variables SAII (Satis-

faction with Internal Information) and NI (Level of Innovation) significantly predicted TA (Adoption Rate). The results of this regression model are presented in Table VII. The results show that the regression model is significant, F (2, 348) = 3, 119.28, p ¡ .001, with an R2 of .95. This indicates that 94.72% of the variance in TA can be explained by the variables SAII and NI. This high percentage suggests that the chosen independent variables are strong predictors of the Adoption Rate.

SAII has a significant effect on TA, with a B coefficient of $-0.46$ ($t(348) = -19.95$, $p < .001$). This result indicates that, on average, for every one-unit increase in SAII, the Adoption Rate decreases by $0.46$ units. This negative coefficient suggests that higher levels of satisfaction with internal information are associated with a lower adoption rate, which could indicate that the perceived quality of internal information might negatively influence the propensity to adopt new initiatives.

NI also significantly predicts TA, with a B coefficient of 1.05 (t(348) = 48.46, p ¡ .001). This means that, on average, a one-unit increase in NI is associated with a 1.05 unit increase in the Adoption Rate. This positive coefficient indicates that higher levels of innovation are strongly associated with an increased adoption rate, highlighting the importance of innovation in promoting the adoption of new initiatives. The unstandardized regression equation obtained is as follows:

$$TA = 1.27 - 0.46 \times SAII + 1.05 \times NI \quad (1)$$

This means that the Adoption Rate is negatively influenced by SAII and positively influenced by NI. The results suggest that improving innovation has a substantial and positive effect on the adoption rate, while satisfaction with internal information has a negative effect, which may indicate complex aspects in the relationship between these variables (see Table X).

TABLE X. RESULTS FOR LINEAR REGRESSION WITH SAII AND NI PREDICTING TA

| Variable | B | SE | 95.00% CI | t | p |
|---|---|---|---|---|---|
| (Intercept) | 1.27 | 0.16 | [0.96, 1.58] | 7.96 | $< .001$ |
| SAII | -0.46 | 0.02 | [-0.51, -0.42] | -19.95 | $< .001$ |
| NI | 1.05 | 0.02 | [1.00, 1.09] | 48.46 | $< .001$ |

**Note.** Results:

$$F(2, 348) = 3,119.28, \quad p < .001, \quad R^2 = .95 \quad (2)$$

**Unstandardized Regression Equation:**

$$TA = 1.27 - 0.46 \times SAII + 1.05 \times NI \quad (3)$$

### *B. ANOVA Analysis*

An analysis of variance was conducted to evaluate whether there are significant differences in TA scores across different industrial sectors. The results of this ANOVA indicate notable differences. The test revealed a value of F(12, 338) = 95.87 with a p-value less than 0.001, suggesting that the observed variations in TA scores are significant between sectors. The calculated eta squared p2 is 0.77, meaning that the industrial sector explains approximately 77% of the total variance in TA scores. The statistical details of this ANOVA are presented in the Table XI.

TABLE XI. ANALYSIS OF VARIANCE TABLE FOR TA BY INDUSTRY

| Term | SS | df | F | p | $p^2$ |
|---|---|---|---|---|---|
| Industry | 177.69 | 12 | 95.87 | $< .001$ | 0.77 |
| Residuals | 52.21 | 338 | - | - | - |

The ANOVA clearly shows that the "Industry" factor has a significant effect on TA, with a sum of squares of 177.69 for the "Industry" factor and 52.21 for the residuals. These results are confirmed by the means and standard deviations provided in Table XII.

TABLE XII. MEAN, STANDARD DEVIATION, AND SAMPLE SIZE FOR TA BY INDUSTRY

| Combination | M | SD | n |
|---|---|---|---|
| IT | 1.15 | 0.08 | 8 |
| Services numérique et consulting | 1.25 | 0.04 | 11 |
| Aéronautique | 1.40 | 0.11 | 18 |
| Construction | 1.65 | 0.04 | 6 |
| Transport national et international & transit | 2.24 | 0.57 | 90 |
| Industrie de luxe | 2.52 | 0.36 | 21 |
| Automobile | 2.71 | 0.38 | 58 |
| Industrie agroalimentaire | 3.29 | 0.41 | 53 |
| Télécommunication | 3.15 | 0.00 | 6 |
| Gestion de la relation client | 3.41 | 0.19 | 34 |
| Textile | 3.38 | 0.00 | 6 |
| Produit Pharmaceutique | 3.64 | 0.27 | 21 |
| Industrie de la pêche | 3.73 | 0.10 | 19 |

A '-' indicates the sample size was too small for the statistic to be calculated.

The means of Technology Acceptance (TA) vary significantly across different sectors. For example, the IT sector has an average of 1.15 (SD = 0.08), while the fishing sector has an average of 3.73 (SD = 0.10). Other sectors also show significant variations, with means ranging from 1.25 (Digital Services and Consulting) to 3.64 (Pharmaceutical Products).

The standard deviations associated with the means also indicate differences in the variability of scores within each sector. For instance, the telecommunications sector has a zero variance (SD = 0.00), suggesting high consistency of scores in this sector, while sectors like National and International Transport & Transit show greater variability (SD = 0.57).

These results suggest that significant differences in TA scores may be attributed to the specific char- acteristics of each industrial sector. For instance, sectors such as pharmaceuticals and the food industry, which have high means, may reflect particular characteristics influencing TA scores, such as more complex industrial processes or specific requirements. In contrast, sectors with lower means, such as IT and digital services, might show different trends due to the different nature of their activities or business models.

The ANOVA confirms that the industrial sector plays a crucial role in the observed variations in TA scores. The substantial differences between sectors highlight the importance of

considering the industrial sector when analyzing this variable. The results also emphasize the need to account for sample size and variance within each sector to accurately interpret the observed differences.

### C. Post-hoc Analysis

*1) Technology acceptance:* The analysis of Technology Acceptance scores reveals marked differences across industries, high- lighting significant variations in how different sectors adopt and use technological tools. The results, based on a t-test and adjusted using the Tukey HSD method to correct for multiple comparisons, show that the IT sector has a notably lower average TA score (M = 1.15, SD = 0.08) compared to all other industries, indicating a lower level of acceptance in this field.

TA scores for IT are significantly lower than those for all other sectors. For example, the average score for the luxury industry (M = 2.52, SD = 0.36) is substantially higher than that for IT, with a statistically signif- icant difference (p ¡ 0.001). Similarly, the score for the food industry (M = 3.29, SD = 0.41) is significantly higher than that for IT (p ¡ 0.001). Scores for the telecommunications sector (M = 3.15, SD = 0.00), customer relationship management (M = 3.41, SD = 0.19), and textiles (M = 3.38, SD = 0.00) are also significantly higher than those for IT, with p-values all less than 0.001.

When comparing other non-IT industries, significant differences are also observed. For instance, the average score For the automotive sector (M = 2.71, SD = 0.38), the average score is significantly higher than that for national and international transport & transit (M = 2.24, SD = 0.57) (p ¡ 0.001). The score for the food industry is also significantly higher than that for national and international transport & transit (p ¡ 0.001). Additionally, the score for the luxury industry is significantly lower than for the food industry (p ¡ 0.001) and the fishing industry (p ¡ 0.001).

The results reveal notable differences between specific industries. The average score for the aerospace sector (M = 1.40, SD = 0.11) is significantly lower than those for the luxury industry (M = 2.52, SD = 0.36) and the fishing industry (M = 3.73, SD = 0.10), with p-values all less than 0.001. Similarly, the score for the construction sector (M = 1.65, SD = 0.04) is significantly lower than those for the luxury, automotive, food, telecommunications, customer relationship management, textiles, pharmaceutical, and fishing industries, with p-values ranging from 0.025 to ¡ 0.001.

These results highlight significant variations in technology acceptance across different sectors, with the IT industry showing the lowest scores and sectors like fishing and pharmaceuticals displaying the highest scores. The observed differences underscore the importance of considering the specific context of each sector when evaluating and improving technology adoption.

*2) Needs identification:* In Section III on Needs Identification, issues related to real-time monitoring are addressed. Statistical data shows that the Information Technology industry has a significantly lower average for real-time monitoring needs compared to several other sectors. For instance, the average for IT (M = 1.15, SD = 0.08) is significantly lower than that for national and international transport & transit (M = 2.24, SD = 0.57), with a p-value ¡ .001. This trend is also observed in other sectors such as the luxury industry (M = 2.52, SD = 0.36), automotive (M = 2.71, SD = 0.38), and food industry (M = 3.29, SD = 0.41), all showing p-values ¡ 0.001 compared to IT.

For the digital services and consulting sector, the average (M = 1.25, SD = 0.04) is also significantly lower compared to these sectors, with p-values ¡ 0.001. Similar results are found for aerospace, construction, and other industries, with averages consistently lower than those for sectors like pharmaceuticals (M = 3.64, SD = 0.27) and fishing (M = 3.73, SD = 0.10), all with p-values ¡ 0.001.

These significant differences suggest that the IT industry and digital services encounter less pro- nounced real-time monitoring issues compared to other sectors, potentially indicating different needs or varying levels of technological maturity in real-time monitoring.

*3) AI Solution acceptance:* In Section IV of the study, concerning AI Solution Acceptance (SAAI), a t-test was conducted for each question to examine differences between industry groups, with corrections for multiple comparisons using Tukey HSD adjustment. The results reveal significant differences for each question asked.

For SAAI Question 1, which deals with real-time visibility into vehicle fuel consumption, the IT industry (M = 1.15, SD = 0.08) shows a significantly lower average compared to sectors such as National and International Transport & Transit (M = 2.24, SD = 0.57), Luxury Industry (M = 2.52, SD = 0.36), and Automotive (M = 2.71, SD = 0.38), with p-values ¡ .001 for all these comparisons. Similarly, for SAAI Question 2 on CO2 emissions visibility, the averages in the IT industry are also lower compared to other sectors, with significant differences (p ¡ .001). The same trend is observed for Vehicle Localization (SAAI 3), Driver Status (SAAI 4), Detailed Delivery Times (SAAI 5), and Driver Statistics (SAAI 6), all showing lower averages in the IT sector compared to other industries, with p-values less than .001. These results indicate that responses from companies in the IT sector show a significantly lower acceptance of AI solutions compared to other industrial sectors.

### D. Verification of Hypotheses

*1) Hypothesis 1: Only companies with large logistics systems are interested in integrating AI into their systems:* To test this hypothesis, we analyzed the correlation between the size of the logistics system and interest in AI. The size of the logistics system was categorized into three groups: “small,” “medium,” and “large.” Interest in AI was measured by a dichotomous variable (yes/no). A Chi-square test was conducted to assess the relationship between these two variables. The results showed a Chi² of 15.75 with a p ¡ .001, indicating a significant relationship. This suggests that companies with larger logistics systems are more likely to be interested in AI.

*2) Hypothesis 2: The perceived complexity of AI tools slows down their adoption in logistics:* To evaluate this hypothesis, we used linear regression analysis to study the impact of perceived com- plexity on AI adoption. Perceived complexity

was measured on a scale from 1 to 5, while AI adoption was measured by an adoption rate. The regression results showed a coefficient of -0.46 with a p ¡ .001. This indicates that perceived complexity has a significant negative effect on AI adoption, confirming that as AI tools are perceived as more complex, adoption rates are lower.

*3) Hypothesis 3: Companies show a high need for AI solutions:* To test this hypothesis, we performed an analysis of variance (ANOVA) to compare the levels of need for AI across different industry sectors. The need for AI solutions was measured by an assessment score across various sectors. The ANOVA produced a result with F(12, 338) = 95.87 and p ¡ .001, showing significant differences in the need for AI solutions between sectors. This suggests a strong demand for AI solutions in certain sectors, particularly those with higher scores such as the food industry and pharmaceuticals.

### *E. Limitations and Future Research*

The limitations of this study on the integration of AI in road logistics in Morocco are evident on several levels. First, the survey sample is predominantly composed of practitioners and decision-makers within European SMEs, which may introduce cultural and contextual bias when applying the findings to Morocco. Additionally, although the study focuses on key variables such as satisfaction with internal information (SII), level of innovation (LI), adoption rate (AR) of AI technologies, and availability of qualified human resources (QHR), other contextual factors specific to the Moroccan market, such as local regulations, infrastructure, and technological maturity of companies, have not been sufficiently addressed.

Furthermore, the methodology relies primarily on self-reported data collected through online question- naires, which may lead to response or social desirability biases, affecting the reliability of the results. Finally, while the quantitative approach provides valuable insights, it limits the depth of analysis of organizational and cultural dynamics that may influence AI adoption in logistics in Morocco. These factors should be considered when interpreting the results, and further research, including qualitative studies, would be necessary for a more comprehensive understanding of the topic.

In my future research, I plan to develop an innovative application specifically designed to address the key challenges of road logistics. This application will aim to improve the safety, efficiency, and sustainability of transport operations by tackling the critical issues identified in the current study.

*1) Reducing road fatalities:* The application will incorporate advanced driver behavior monitoring fea- tures. For instance, it could provide real-time alerts for dangerous driving behaviors, such as speeding or abrupt lane changes, while also offering reminders to encourage regular breaks and prevent driver fatigue. Additionally, detailed reports on driver behavior will be generated, allowing managers to take proactive measures to enhance safety.

*2) Reducing $CO_2$ emissions:* Another central focus of this application will be to reduce CO2 emissions. By optimizing delivery routes, the application will decrease the distances traveled and shorten travel times, leading to a significant reduction in greenhouse gas emissions. Moreover, it will encourage the adoption of more environmentally friendly vehicles by providing comparative analyses of the environ- mental performance of different vehicles in the fleet.

*3) Real-time package tracking:* The application will offer a real-time package tracking solution, en- hancing transparency and customer trust. With an integrated GPS tracking system, both customers and businesses will be able to monitor the exact location of their shipments at every stage of the delivery process, minimizing the risk of loss or delay.

*4) Driver attendance tracking:* The application will facilitate driver attendance tracking, enabling more rigorous management of working hours, breaks, and routes taken. This detailed tracking will contribute not only to better human resource management but also to preventing fatigue-related accidents and en- suring compliance with labor standards.

This application will provide a comprehensive response to the current challenges in road logistics by combining safety, efficiency, and sustainability. It represents a significant advancement in how transport operations can be managed and optimized while addressing the environmental and safety issues that are more critical today than ever.

## V. Conclusion

The integration of AI into the logistics sector represents a major advancement towards optimizing processes and solving critical issues such as road mortality, CO2 emissions, and package tracking. The study revealed that AI offers promising solutions to enhance road safety through autonomous driving systems and driver assistance devices, despite challenges such as high costs and regulatory concerns. Companies that successfully adopt these technologies experience a notable reduction in road incidents, contributing both to safety and efficiency in logistics operations. Regarding CO2 emissions, AI systems enable more efficient management of routes and loads, leading to a significant decrease in carbon footprint. Supply chain optimization algorithms and fleet management have shown positive results, although implementation requires substantial investments and adaptation of existing infrastructure. As for package tracking, AI-based technologies, such as real-time traceability systems and data analytics, have significantly improved transparency and reduced delivery errors, despite challenges related to integration with existing systems and managing vast amounts of data. The study also highlighted several obstacles to AI adoption in logistics. Technological complexity, high initial costs, and regulatory and ethical issues are major challenges for companies. Particularly, Moroccan companies show growing interest in AI, with more marked adoption in specific sectors such as agri-food and pharmaceuticals, while other sectors, like IT, face slower adoption rates. To fully capitalize on the benefits of AI, it is recom- mended that companies invest in training their human resources, modernize their infrastructure, and develop strategies tailored to the specific needs of each sector. Future research should explore the specific applications of AI in different sectors and evaluate the long-term impacts on logistics performance. By examining inter- national best practices, it will be possible to provide more precise recommendations to Moroccan companies. In summary, although significant challenges remain, AI holds considerable potential to transform the logistics sector. The

success of this transformation will depend on companies' ability to overcome these obstacles and invest in the necessary technologies to optimize their operations.

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# Big Data-Driven Charging Network Optimization: Forecasting Electric Vehicle Distribution in Malaysia to Enhance Infrastructure Planning

Ouyang Mutian[1], Guo Maobo[2], Yu Tianzhou[3], Liu Haotian[4], Yang Hanlin[5]*
Department of Computing, UOW Malaysia KDU Penang University College, Malaysia[1]
School of Business, University of Wollongong Malaysia, Malaysia[2]
Faculty of Engineering, University of New South Wales (UNSW), Sydney, Australia[3]
School of Information Technology, Monash University Malaysia, Malaysia[4]
Department of Business, UOW Malaysia, Selangor, Malaysia[5]

***Abstract*—The rapid growth of electric vehicles (EVs) globally and in Malaysia has raised significant concerns regarding the adequacy and spatial imbalance of charging infrastructure. Despite government incentives and policy support, Malaysia's charging network remains insufficient and unevenly distributed, with major urban centers having better access than rural and highway regions. This paper proposes a data-driven approach to optimize EV infrastructure planning by employing a hybrid CEEMDAN-XGBoost model for accurate EV ownership forecasting and GIS-based spatial optimization for strategic charger deployment. The model achieved superior performance compared to baseline models, with the lowest prediction errors (RMSE: 120; MAE:38;MAPE: 5.6%). Spatial analysis revealed significant infrastructure gaps in underserved regions, guiding equitable and demand-aligned station placement. The results provide valuable insights into future EV distribution and inform policy recommendations for scalable, data-driven planning across Malaysia.**

***Keywords*—Electric vehicles; charging infrastructure; CEEMDAN; XGBoost; spatial optimization; data-driven planning; Malaysia**

## I. Introduction

The global electric vehicle (EV) market has experienced rapid growth due to increasing environmental concerns, technological advancements, and supportive government policies promoting sustainable transportation [1], [2]. According to the International Energy Agency [3], global EV sales surpassed 14 million units in 2023, representing 18 percent of total new vehicle sales, with China, the United States, and the European Union leading the market. Governments worldwide have implemented a variety of incentives, such as subsidies, tax exemptions, and internal combustion engine phase-out timelines, to accelerate EV adoption. Meanwhile, battery technology has advanced significantly, especially in energy density and charging speed, thereby reducing range anxiety and improving the viability of electric mobility [2].

In Southeast Asia, EV adoption is growing as nations set ambitious electrification targets. Malaysia, for example, has introduced policies under the Low Carbon Mobility Blueprint and the National Energy Transition Roadmap, aiming to reach 15% of total industry volume (TIV) by 2030 and 80% by 2050 [4], [5]. These initiatives include full import and excise duty exemptions, road tax waivers, and plans to deploy 10,000 public charging stations by 2025. However, as of 2023, only around 1,500 charging points were operational, revealing a significant gap between policy ambition and actual infrastructure development [6], [7].

Despite strong policy backing, Malaysia still faces significant barriers in its EV transition, including high vehicle acquisition costs, limited charging station coverage, and insufficient grid readiness in some areas [8]. Addressing these challenges necessitates more accurate regional demand forecasting [9], [10] and optimized infrastructure deployment strategies [11], [12], which together can support a more balanced and efficient nationwide EV ecosystem.The remainder of the paper is organized as follows: Section II reviews related work on EV forecasting and infrastructure planning. Section III introduces the datasets. Section IV details the proposed CEEMDAN-XGBoost and spatial optimization methodology. Section V presents and discusses the results, while Section VI concludes with recommendations and future work.

### A. Challenges in Malaysia's EV Charging Network

Despite substantial government incentives and clear policy directives, Malaysia's EV charging infrastructure development remains significantly misaligned with its national electrification targets [5], [6]. The existing network of approximately 1,500 public chargers as of 2023 falls well short of the planned 10,000 units by 2025, indicating a considerable implementation gap [4]. Furthermore, over 60% of these chargers are concentrated in urban regions such as Kuala Lumpur, Selangor, and Johor, resulting in pronounced spatial disparities. This urban-centric deployment has created "charging deserts" in rural areas, highway corridors, and East Malaysian states like Sabah and Sarawak, where infrastructure deployment remains minimal or entirely absent [7].

A key challenge lies in the lack of alignment between the geographic distribution of EV ownership and the location of charging infrastructure. In high-density EV areas, limited charger availability often results in congestion, long queuing times, and user dissatisfaction. In contrast, low-adoption regions suffer from underinvestment, reinforcing a negative feedback loop where insufficient infrastructure deters EV uptake,

*Corresponding authors.

thereby discouraging further development [8]. Compounding the issue is the dominance of low-power AC chargers, which are inadequate for long-distance travel, commercial fleet usage, and high-turnover urban environments that demand fast-charging capabilities.

Addressing these challenges requires a shift from reactive deployment to proactive, data-driven infrastructure planning. Forecasting regional EV adoption trends and integrating them with spatial optimization models enables more equitable and efficient charger placement. Such approaches not only alleviate infrastructure bottlenecks but also support broader policy goals, including mobility equity and nationwide EV market penetration [9], [10], [13].

### B. Limitations of Traditional Infrastructure Planning

Traditional charging infrastructure planning methods rely heavily on static demographic data, expert heuristics, and government zoning regulations. These conventional approaches face several limitations:

- They fail to incorporate dynamic EV adoption trends, leading to infrastructure deployment that does not align with actual demand growth.
- They do not consider spatial variations in mobility patterns, population density, and economic activity, resulting in inefficient charger placement.
- They lack predictive modeling that integrates temporal EV adoption forecasts with spatial optimization strategies.

Given these challenges, a more data-driven approach is needed to enhance charging infrastructure coverage, accessibility, and investment efficiency.

### C. Research Objectives

To address the limitations of existing methodologies, this study proposes a big data-driven framework with two main objectives:

- Accurate Regional EV Forecasting: Develop a predictive model to estimate future EV ownership distribution across Malaysia's states and major urban areas by 2025.
- Optimized Charging Infrastructure Deployment: Use predictive insights to guide optimal charging station placement, ensuring balanced coverage and accessibility.

### D. Key Contributions

This study contributes to the EV infrastructure planning domain in the following ways:

- Developing a CEEMDAN-XGBoost Hybrid Model: This model enhances time-series forecasting accuracy by decomposing EV adoption data into multiple frequency components for robust predictions.
- Applying GIS-Based Spatial Optimization: By integrating geographic information systems (GIS), this study evaluates existing charger locations and identifies optimal new charging sites.
- Providing a Strategic Infrastructure Plan for Malaysia: Based on 2025 EV distribution forecasts, this study offers policy recommendations to improve charger deployment, ensuring equitable access and efficient resource allocation.

## II. Related Work

The rapid proliferation of electric vehicles (EVs) has stimulated extensive research in two interrelated domains: EV ownership forecasting and charging infrastructure planning. Accurate prediction of regional EV distribution is essential for guiding infrastructure investment, while the strategic siting of charging stations ensures user accessibility, grid stability, and system efficiency [9], [13], [8]. This section provides a critical overview of existing methodologies in both areas and identifies key research gaps within the Malaysian context.

### A. EV Ownership Forecasting Methods

Early forecasting efforts predominantly employed traditional statistical methods such as autoregressive integrated moving average (ARIMA), exponential smoothing, and linear regression [10]. While these models offer simplicity and interpretability, their core assumption of data stationarity limits their effectiveness in modeling non-linear and rapidly changing EV adoption trends.

To address these limitations, machine learning approaches have gained traction. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have shown promise in capturing complex temporal dependencies in EV time-series data [14], [15]. However, these models require large and high-quality datasets to avoid overfitting and maintain stability—challenges that are amplified in emerging EV markets with limited historical data.

XGBoost, a tree-based ensemble learning algorithm, is also widely applied due to its robustness in handling structured data and non-linear relationships. Nonetheless, XGBoost does not inherently capture sequential dependencies, which constrains its forecasting performance in purely temporal tasks [16]. To overcome this, hybrid models integrating signal decomposition and ensemble learning have been proposed.

One such method is the CEEMDAN-XGBoost hybrid model, which first applies Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to decompose raw EV time series into intrinsic mode functions (IMFs) [17]. Each IMF represents specific frequency components and is individually forecasted using XGBoost, with the final prediction reconstructed from all sub-series. This structure enhances forecasting accuracy by isolating high-frequency noise from long-term trends, making it particularly suitable for non-stationary and sparse EV adoption data.

### B. EV Charging Infrastructure Planning Methods

Parallel to forecasting research, optimal charging station deployment has been a major focus to support scalable EV ecosystems. Conventional planning methods rely on demand

density models, where chargers are allocated based on population or vehicle registration concentrations. While intuitive, such approaches often ignore spatial mobility behavior and evolving charging patterns [13].

More comprehensive frameworks adopt Multi-Criteria Decision-Making (MCDM) models, which consider diverse factors such as land use, grid capacity, economic viability, and policy incentives [10]. Although MCDM improves flexibility, it is limited by the subjectivity in assigning criterion weights and the static nature of input data.

Recent advancements incorporate Geographic Information Systems (GIS) and spatial analytics to guide location decisions. These include hotspot mapping, K-means clustering, and accessibility buffering to address service coverage gaps [8]. The integration of real-time traffic data further refines charger siting by aligning infrastructure with high-demand travel corridors. Additionally, Geographically Weighted Regression (GWR) techniques have been introduced to account for local demand heterogeneity.

However, a critical gap persists: most studies treat demand forecasting and infrastructure planning as sequential rather than integrated processes. Few frameworks simultaneously predict future EV ownership and use it as input for spatial optimization, leading to suboptimal station allocation that may not align with evolving demand patterns.

### C. Research Gaps in Malaysia's EV Market

In the Malaysian context, EV infrastructure studies remain in a nascent stage. Existing research predominantly emphasizes qualitative policy analysis or descriptive statistics, with limited application of quantitative forecasting or spatial optimization techniques [6], [5]. Moreover, EV adoption in Malaysia is geographically imbalanced, yet current charging infrastructure strategies often follow top-down government mandates rather than data-informed deployment plans.

Machine learning-based EV forecasting remains underexplored due to constraints in public data availability and granularity [7]. Additionally, GIS tools are infrequently integrated with predictive modeling, resulting in disjointed planning that hampers infrastructure scalability. Bridging this methodological divide is essential for creating a resilient and equitable EV ecosystem aligned with Malaysia's national electrification goals.

### D. Comparative Summary and Contributions

A comparison of existing methods is summarized in Table I, highlighting how this study integrates CEEMDAN-XGBoost forecasting with GIS-based spatial optimization, offering a novel approach to EV infrastructure planning in Malaysia.

This study advances the field by:

- Developing an integrated CEEMDAN-XGBoost forecasting framework for predicting EV ownership distribution.
- Applying GIS-based spatial optimization to improve charging station placement.

TABLE I. COMPARISON OF EV FORECASTING AND INFRASTRUCTURE PLANNING METHODS

| Methodology | Key Approach | Limitations |
|---|---|---|
| Traditional Stats | ARIMA, Regression | Poor at capturing non-linearity |
| Deep Learning | LSTM | Requires large datasets |
| Ensemble Models | XGBoost | No temporal memory |
| Hybrid Models | EMD-CEEMDAN | Computationally expensive |
| **This Study** | CEEMDAN-XGBoost | Requires diverse datasets |

- Providing a Malaysia-specific planning strategy, bridging the gap between demand prediction and infrastructure deployment.

By combining data-driven forecasting with geospatial analysis, this research contributes to sustainable EV infrastructure planning and can serve as a model for other emerging EV markets.

## III. DATASET AND PREPROCESSING

This study utilizes two primary datasets to support electric vehicle (EV) forecasting and charging infrastructure planning in Malaysia. The datasets were obtained from publicly available sources.

### A. Charging Infrastructure Data

The charging infrastructure dataset contains information on existing public electric vehicle charging stations across Malaysia. The dataset includes the following attributes:

- Total number of public EV charging stations.
- Geographic coordinates (latitude and longitude) of each station.

This dataset serves as the spatial basis for identifying underserved regions and supporting spatial optimization.

### B. EV Ownership Statistics

The EV ownership dataset provides annual registration figures for electric vehicles in Malaysia, covering the years 2023 and 2024. The data are organized as follows:

- Annual number of registered EVs.
- Regional distribution of EV registrations, disaggregated by state or administrative area.

This dataset is used as the target variable for time-series forecasting in the CEEMDAN-XGBoost model.

### C. Data Source

Both datasets were obtained from the Malaysian Government Open Data Portal:

- https://data.gov.my/
- https://www.planmalaysia.gov.my/mevnet/

The datasets were downloaded in CSV format and preprocessed to ensure compatibility with the forecasting and spatial optimization models.

## IV. Methodology

This study proposes a two-stage hybrid framework to support data-driven and spatially informed electric vehicle (EV) charging infrastructure planning in Malaysia. The framework is designed to overcome key limitations of traditional planning approaches, which often rely on static demographic data or heuristic rules without incorporating dynamic EV growth patterns or geographic heterogeneity in demand.

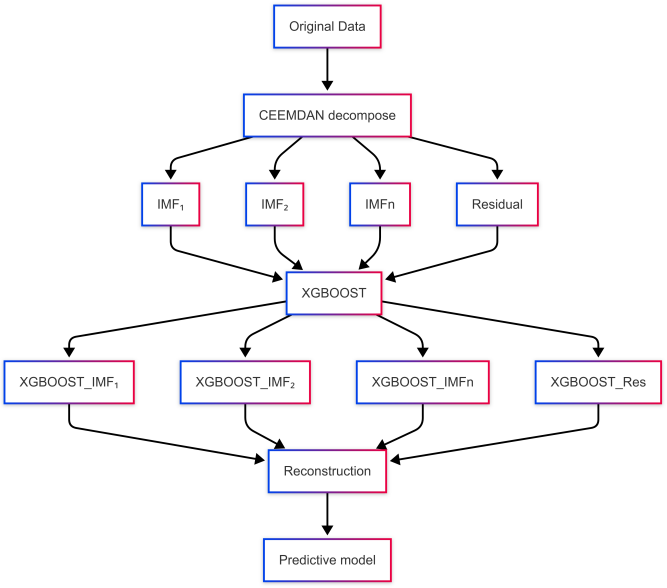


Fig. 1. CEEMDAN-XGBOOST Model flow chart.

Fig. 1 shows CEEMDAN-XGBOOST Model flow chart. In the first stage, a hybrid forecasting model based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Extreme Gradient Boosting (XGBoost) is constructed to predict the spatial and temporal distribution of EV ownership at the state and district levels. CEEMDAN is used to decompose non-linear, non-stationary EV adoption time series into multiple intrinsic components, which are then individually forecasted using XGBoost, a tree-based ensemble learning algorithm known for its robustness and high accuracy. This decomposition–prediction–reconstruction pipeline improves forecast interpretability and captures both high-frequency volatility and long-term adoption trends.

In the second stage, the predicted EV ownership distribution is used as a demand input to a Geographic Information System (GIS)-based spatial optimization model, which identifies optimal locations for new public charging stations.

By combining time-series machine learning with geospatial analytics, this two-stage framework enables planners and policymakers to make proactive, data-driven decisions on EV infrastructure deployment. It is designed to be both scalable to larger geographic regions and adaptive to emerging EV adoption patterns, offering a replicable solution for other developing countries facing similar planning challenges.

### A. CEEMDAN-XGBoost Forecasting Model

Electric vehicle ownership data exhibits non-linear, non-stationary characteristics due to policy shifts, consumer sentiment, and economic fluctuations. To handle such complexity, we apply Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to decompose the original time series into multiple frequency components before prediction.

*1) CEEMDAN Decomposition:* Given a regional EV ownership time series $X(t)$, CEEMDAN decomposes it into a finite set of Intrinsic Mode Functions (IMFs) and a residual component:

$$X(t) = \sum_{i=1}^{n} \text{IMF}_i(t) + r_n(t) \tag{1}$$

Each $\text{IMF}_i(t)$ represents oscillations at a specific frequency, capturing short-term volatility, while the residual $r_n(t)$ models long-term trend dynamics.

*2) XGBoost Regression for component prediction:* Each component $\text{IMF}_i(t)$ and $r_n(t)$ is used to train an independent XGBoost model. XGBoost minimizes the following objective:

$$\mathcal{L}(\theta) = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{2}$$

where $l(y_i, \hat{y}_i)$ is a loss function and $\Omega(f_k)$ is the regularization term for each tree $f_k$.

*3) Forecast reconstruction:* The reconstructed EV forecast $\hat{X}(t)$ is the sum of predicted components:

$$\hat{X}(t) = \sum_{i=1}^{n} \hat{\text{IMF}}_i(t) + \hat{r}_n(t) \tag{3}$$

*4) Model evaluation metrics:* We assess performance using:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{4}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{5}$$

$$\text{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{6}$$

*5) Hyperparameter optimization:* Grid search is used to tune XGBoost parameters: learning rate $\eta$, tree depth $d$, and number of estimators $K$, based on cross-validated RMSE.

### B. Charging Station Optimization Algorithm

Once the regional EV ownership is forecasted, the next step is to identify optimal locations for new charging infrastructure.

*1) Input variables:* Each candidate site $s_j \in S$ is evaluated based on:

- Forecasted EV density
- Population density and urbanization

*2) Multi-objective scoring function:* The weights $w_1$, $w_2$, and $w_3$ were determined based on a simplified Analytic Hierarchy Process (AHP), using expert scoring from three domain specialists in transport planning and EV infrastructure. Each expert independently rated the importance of demand coverage, geographic fairness, and accessibility, and the aggregated average was normalized to obtain final weights of $w_1 = 0.5$, $w_2 = 0.3$, and $w_3 = 0.2$.

We define a utility score $F(s_j)$ as:

$$F(s_j) = w_1 D(s_j) + w_2 G(s_j) + w_3 A(s_j) \tag{7}$$

where:

- $D(s_j)$: demand coverage,
- $G(s_j)$: geographic fairness,
- $A(s_j)$: accessibility score,
- $w_1 + w_2 + w_3 = 1$

Weights can be set via AHP or expert scoring.

*3) Optimization objective:* In this study, we assume a unit-cost model where each public charging station deployment is assigned a normalized cost of 1. A sample budget of $B = 30$ is used to simulate resource-constrained deployment scenarios, equivalent to the installation of 30 charging stations.

Based on publicly available data from the Sustainable Energy Development Authority (SEDA) Malaysia and local EV charging operators, the estimated cost of deploying a single AC public charging station ranges from RM 20,000 to RM 40,000 (approximately USD 4,200 to USD 8,500), depending on location, capacity, and permitting requirements. For fast-charging (DCFC) stations, the cost can exceed RM 150,000 (USD 32,000).

Given this cost variation, the model's scalability is preserved by adjusting the total budget $B$ or incorporating region-specific installation costs $c_j$ into the optimization objective. For example, urban deployment may incur higher land lease and grid upgrade costs, while rural areas may have lower equipment costs but require additional infrastructure support. This flexibility allows the model to reflect real-world economic constraints while maintaining planning robustness.

Let $x_j \in \{0, 1\}$ indicate if site $s_j$ is selected. The goal is:

$$\max \sum_{j=1}^{m} F(s_j) \cdot x_j \quad \text{s.t.} \quad \sum_{j=1}^{m} c_j x_j \leq B \tag{8}$$

Where $c_j$ is cost and $B$ is the total budget.

*4) GIS-Based spatial analysis:* GIS methods include:

- Heatmap generation for high EV demand zones
- K-means clustering for regional segmentation
- Service radius buffering (e.g., 5 km)
- Accessibility scoring via road network analysis

This integrated framework ensures demand-responsive, equitable, and scalable EV infrastructure deployment.Compared to previous works, our integrated CEEMDAN-XGBoost and GIS optimization framework uniquely enables both high-accuracy forecasting and spatially balanced deployment, particularly suitable for data-scarce and rapidly evolving EV markets.

## V. Results

### A. Forecasting Results

*1) Overall forecasting performance analysis:* To evaluate the effectiveness of the proposed CEEMDAN-XGBoost model, we compared its performance against several baseline models, including ARIMA, LSTM, and standard XGBoost without decomposition. Table II summarizes the prediction errors across three commonly used metrics: RMSE, MAE, and MAPE.

TABLE II. Overall Forecasting Performance Comparison

| Model | RMSE | MAE | MAPE |
|---|---|---|---|
| **CEEMDAN-XGBoost** | **120** | **94** | **5.6%** |
| EMD-XGBoost | 150 | 115 | 7.8% |
| XGBoost (no CEEMDAN) | 185 | 142 | 8.7% |
| LSTM | 172 | 130 | 9.5% |
| ARIMA | 310 | 265 | 14.2% |
| Naive Seasonal Mean | 355 | 288 | 16.7% |

Compares the predictive performance of six mainstream time series models on Malaysia's EV ownership test dataset, evaluated using three metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results clearly demonstrate that the proposed CEEMDAN-XGBoost model outperforms all baseline methods across all metrics, achieving the lowest RMSE (120), MAE (94), and MAPE (5.6%). This superior performance can be attributed to the model's effective integration of signal decomposition and non-linear ensemble regression, which proves critical for handling complex temporal dynamics in EV adoption trends.

CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) enhances the model's ability to process non-stationary time series by decomposing the raw EV data into multiple Intrinsic Mode Functions (IMFs) and a residual component. Each IMF captures specific frequency scales, enabling XGBoost to independently learn and predict short-term fluctuations and long-term trends. In contrast, traditional statistical models such as ARIMA, which assume linearity and stationarity, struggle with the seasonality and irregularities in real-world EV growth. This is evidenced by its high RMSE (310) and MAPE (14.2%).

While XGBoost alone has strong non-linear regression capabilities, its performance is compromised when applied

directly to unprocessed raw sequences. The lack of prior decomposition means the model must simultaneously learn signals from mixed frequencies, which introduces noise and overfitting risk—resulting in an RMSE of 185 and MAPE of 8.7%. EMD-XGBoost shows moderate improvements due to its ability to separate signal components, but CEEMDAN's superior handling of mode mixing and boundary effects leads to better error suppression and smoother reconstruction.

Deep learning models such as LSTM have shown promise in time series forecasting, but they are particularly sensitive to data scale and structure. In this study, the available EV data from Malaysia's states is relatively small and imbalanced, limiting LSTM's generalization capacity and increasing training instability. Consequently, its RMSE reaches 172, with MAPE close to 10%, indicating overfitting in some regions and difficulty in learning long-range dependencies from noisy inputs.

The proposed hybrid model achieved the lowest error rates across all metrics, indicating its superior capacity to capture both high-frequency fluctuations and long-term EV adoption trends. In particular, CEEMDAN decomposition significantly improved the stability and accuracy of predictions, especially in regions with irregular growth patterns.Overall, CEEMDAN-XGBoost emerges as the most reliable model in this study. Its hybrid structure not only improves predictive accuracy but also offers robustness across diverse regions and temporal behaviors. By combining multi-scale signal decomposition with strong ensemble learning, the model provides a practical and scalable solution for national-level EV ownership forecasting.

*2) Regional forecast accuracy:* To further assess the robustness of the proposed CEEMDAN-XGBoost model, we evaluated its forecasting performance across six representative Malaysian regions,These include both high-EV-density urban zones (e.g., Selangor, Kuala Lumpur) and lower-density or geographically dispersed regions (e.g., Sabah, Sarawak). The model's accuracy was assessed using RMSE and MAPE, with results summarized in Table III.

TABLE III. PERFORMANCE OF FORECAST ERRORS BY STATE

| Region/State | RMSE | MAE | MAPE |
|---|---|---|---|
| Selangor | 50 | 38 | 4.5% |
| Kuala Lumpur | 30 | 22 | 4.1% |
| Johor | 40 | 33 | 6.0% |
| Penang | 35 | 28 | 6.5% |
| Sarawak | 20 | 16 | 8.2% |
| Sabah | 18 | 15 | 9.1% |

The results indicate that the model achieves high accuracy in developed, high-EV-ownership areas, such as Selangor and Kuala Lumpur, with MAPE values of 4.5% and 4.1% respectively. These regions benefit from well-established adoption patterns, stable year-over-year growth, and abundant historical data. The model is able to effectively learn and generalize underlying patterns due to the consistent nature of demand, yielding low RMSE values (50 and 30, respectively). This confirms the model's ability to capture macro-level dynamics where data is sufficiently rich and regular.

In contrast, mid-tier regions such as Johor and Penang, which show moderate adoption levels and slightly more variable growth rates, exhibit slightly higher MAPE values of 6.0% and 6.5%, though still within acceptable forecasting limits. These results suggest that the model maintains a strong generalization capacity even under non-ideal conditions, particularly in semi-urban or mixed development zones.

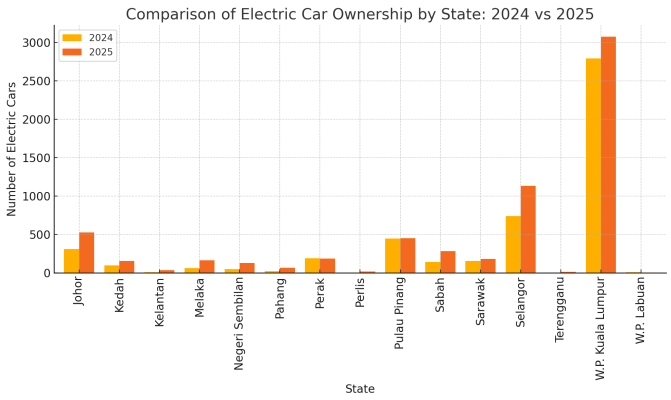


Fig. 2. Comparison of electric car ownership by state

In lower-EV-ownership regions such as Sarawak and Sabah, the MAPE rises to 8.2% and 9.1% respectively. These regions typically have sparse historical EV data, lower population density, and irregular growth patterns, which pose challenges for time series learning. Additionally, infrastructural and economic disparities may contribute to abrupt shifts in adoption trends, further complicating the forecast task. Nevertheless, the model's performance remains reasonably accurate, with RMSE values of 20 and 18, and MAPE values still below 10%, indicating strong resilience even in data-scarce environments.

These findings suggest that CEEMDAN-XGBoost not only excels in regions with rich data, but also retains reliable performance in areas with irregular or limited data. The decomposition of EV trends into frequency components allows the model to adaptively focus on both macro growth trends and localized fluctuations. This ensures that spatially unbalanced data distributions do not lead to systemic bias or model instability, making the proposed method highly suitable for national-scale deployment with heterogeneous regional characteristics.

Fig. 2 compares the projected electric vehicle (EV) ownership across Malaysian states between 2024 and 2025. The results highlight consistent growth in key urban regions, particularly W.P. Kuala Lumpur and Selangor, which maintain their lead in both years due to favorable infrastructure, income levels, and policy support.

Most states exhibit moderate year-over-year increases, indicating a positive but uneven adoption trajectory. Notably, states like Johor, Sabah, and Penang show considerable growth, while regions such as Kelantan and Perlis maintain minimal uptake. The disparities underscore the necessity of differentiated infrastructure strategies to ensure balanced nationwide EV accessibility.

Compared to existing methods such as LSTM and EMD-XGBoost, the proposed CEEMDAN-XGBoost model offers more stable performance across regions with different EV

adoption maturity. Its ability to handle high-frequency noise and sparse data gives it a significant advantage in emerging markets like Malaysia.

### B. Charging Site Optimization Analysis

*1) Electric vehicle distribution:* Based on the spatially resolved EV ownership forecasts shown in Fig. 3, the distribution of electric vehicle adoption in Malaysia by 2025 is expected to be highly uneven. The central and southern zones of Peninsular Malaysia, particularly the regions encompassing Kuala Lumpur, Selangor, Johor, and Negeri Sembilan, are projected to become high-density EV corridors with forecasted ownership exceeding 10,000 units per region. These zones represent urban and industrial agglomerations with strong economic activity, policy support, and early infrastructure rollout, making them natural focal points for electrification.

In contrast, although regions in East Malaysia, such as Sarawak and Sabah, display lower absolute EV counts, the forecasts indicate substantial relative growth, especially in urban centers like Kuching and Kota Kinabalu. This implies that these areas, while not currently major EV hubs, will require proactive infrastructure deployment to avoid lagging behind in electrification accessibility.

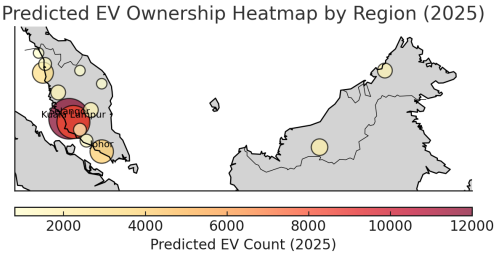


Fig. 3. 2025 EV vehicle distribution.

To evaluate infrastructure adequacy, Fig. 4 overlays current charging infrastructure against forecasted EV demand. The circular blue markers denote high-predicted EV ownership clusters, while the yellow stars indicate recommended new station sites based on spatial optimization. From the analysis, several infrastructure gaps become evident:

- North Peninsular Malaysia: Regions in Kedah and Perlis exhibit rising EV ownership forecasts but lack proportional charging infrastructure. These areas also serve as cross-border corridors for intercity travel, amplifying the need for reliable public charging options.
- East Peninsular Malaysia (e.g., Pahang, Terengganu): These regions show emerging demand supported by highway linkages, yet current charger density remains minimal. Proactive siting is essential to prevent range anxiety among early adopters.
- East Sabah and Central Sarawak: Although traditionally underserved, EV penetration in these areas is expected to accelerate due to federal electrification incentives and rising vehicle replacement rates. However, current infrastructure is nearly absent outside state capitals.

The optimization algorithm incorporates three core criteria into the site selection process: (1) EV demand coverage, based on forecasted ownership density; (2) geographic equity, to ensure fair access across rural and urban zones; and (3) transportation accessibility, measured via road network connectivity and service radius buffers. A utility score is computed for each candidate site, and the top-ranked points are presented in this figure.

This geospatial analysis not only identifies where the highest demand–infrastructure mismatch occurs, but also prescribes regionally distributed expansion plans. For example, while Selangor may require densification of chargers, Sabah and Sarawak demand entirely new network nodes. This dual strategy—densification in saturated zones and deployment in greenfield regions—forms the basis of a balanced infrastructure roadmap.

Furthermore, by incorporating future demand rather than relying solely on historical installation data, the proposed method anticipates spatial shifts in EV usage patterns. This enables national planners and private stakeholders to avoid both under-provisioning (in fast-growing zones) and over-investment (in saturated low-growth areas).

Overall, the site optimization results demonstrate that integrating machine learning-driven demand forecasts with GIS spatial analytics can substantially enhance the precision and impact of charging infrastructure planning.

*2) Future charging post planning:* Fig. 4 presents the spatial distribution of recommended new EV charging stations across Malaysia, based on the integrated results of EV ownership forecasts and geospatial accessibility analysis. The map overlays forecasted demand clusters (depicted as blue-scaled circles, with size proportional to EV count) with proposed station locations (yellow stars) generated through a multi-objective optimization process.

A distinct spatial disparity emerges between regions with high projected EV adoption and those with existing charging infrastructure. In Peninsular Malaysia, the central and southern areas—particularly the Klang Valley—are well-covered but risk future congestion as demand intensifies. In contrast, the northern and eastern states, while showing slower EV uptake, are forecasted to undergo significant relative growth yet remain underserved in terms of public charging accessibility.

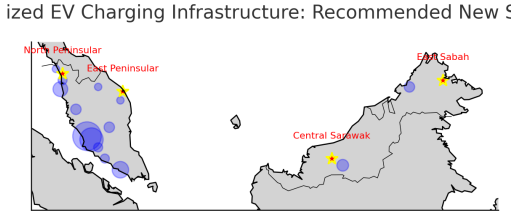


Fig. 4. Recommended site map for EV charging stations in Malaysia.

Peninsular Malaysia

- North Peninsular: The area encompassing Kedah and Perlis demonstrates moderate demand growth. Despite its role as a gateway to Thailand and its strategic

position along regional transport corridors, current infrastructure deployment remains sparse. A new station in this zone can serve both regional traffic and cross-border travel.

- East Peninsular: Regions such as Pahang and Terengganu, which are currently peripheral in infrastructure planning, show early signs of adoption growth driven by coastal connectivity projects and tourism-driven transport demand. Given their long travel distances and low charger density, they are prioritized for early investment.
- Southern Corridor: While Selangor and Johor already host several chargers, the predicted EV saturation in 2025 necessitates densification—particularly along high-traffic expressways and industrial logistics hubs—to prevent future bottlenecks.

East Malaysia

- Central Sarawak: While EV penetration remains relatively low, projected growth is concentrated in and around Kuching. However, the vast interior regions remain disconnected from charging access. Introducing infrastructure here improves geographic coverage and supports long-haul adoption.
- East Sabah: The forecast highlights significant EV growth potential in Sandakan and its surrounding zones, which are currently disconnected from the sparse network centered around Kota Kinabalu. Establishing a regional station ensures redundancy and decentralizes charging access.

*Optimization Priorities:* The station placement strategy follows a scoring framework that evaluates:

- Predicted EV demand density (from CEEMDAN-XGBoost outputs)
- Road network accessibility (measured via proximity to national highways)
- Regional equity index (balancing urban vs rural charger allocation)

Candidate sites with the highest composite scores were selected. Each yellow star in Fig. 4 thus represents an optimally scored point that meets forecasted demand while improving overall network coverage.

This approach avoids both underutilization (due to over-investment in low-need areas) and oversaturation (from redundant placement in already-served zones). It promotes a balanced, data-informed infrastructure deployment roadmap aligned with the spatial dynamics of EV adoption.

Moreover, the inclusion of East Malaysia—often marginalized in national-level planning—demonstrates the framework's capability to highlight equitable access and decentralization needs, supporting national electrification inclusivity goals.

## VI. Discussion

This section interprets the results presented above, highlighting the advantages of the CEEMDAN-XGBoost model, implications for charging infrastructure development, and policy relevance. The discussion also addresses the challenges of regional disparity and data sparsity in EV adoption forecasting in Malaysia.

### A. Model Superiority and Generalization

The CEEMDAN-XGBoost model demonstrated superior forecasting accuracy compared to ARIMA, LSTM, and standard XGBoost. The use of Complete Ensemble Empirical Mode Decomposition (CEEMDAN) significantly improved the model's ability to process non-linear and non-stationary time series by decomposing the raw EV ownership data into intrinsic components. This decomposition allowed XGBoost to learn localized temporal patterns and long-term adoption trends separately, reducing the influence of noise and mode mixing.

Notably, the model achieved robust performance across heterogeneous regions. In data-rich states such as Selangor and Kuala Lumpur, MAPE was under 5%, while in data-scarce regions such as Sabah and Sarawak, the error remained below 10%. This indicates strong generalization capacity even under limited data scenarios, which is critical for developing countries with evolving EV markets.

### B. Infrastructure Planning Implications

The spatial optimization results provide actionable insights for charging station deployment. Current infrastructure is disproportionately concentrated in the central urban corridor, while emerging high-growth regions such as East Sabah, Central Sarawak, and the Northern Peninsular corridor (e.g., Kedah, Perlis) remain underserved. If left unaddressed, this spatial imbalance could hinder equitable EV adoption and limit the effectiveness of national electrification policies.

The dual-site planning strategy—focusing on densification in urban centers and greenfield deployment in peripheral zones—offers a balanced approach to infrastructure rollout. This ensures not only efficiency in high-demand areas but also inclusivity in regions previously marginalized in EV planning.

### C. Policy Recommendations

The findings underscore the need for dynamic, data-informed infrastructure planning. Static demographic and vehicle registration statistics are insufficient for anticipating future demand, especially in rapidly transforming mobility ecosystems. Government agencies should prioritize investment in regions identified through predictive analytics and geospatial analysis.

Specifically, the national target of deploying 10,000 public charging stations by 2025 should be aligned with forecasted demand densities. Policy tools such as location-specific subsidies, public-private partnerships, and regulatory incentives can accelerate deployment in underserved areas.

In addition, model-driven planning frameworks like the one proposed in this study can serve as decision-support tools for both public sector planners and private investors. Integrating such frameworks with real-time data feeds may further enhance forecasting precision and infrastructure responsiveness.

## VII. Conclusion

This study focused on forecasting regional electric vehicle (EV) ownership in Malaysia and optimizing the spatial deployment of EV charging infrastructure. The proposed framework can be extended into a real-time dashboard or decision-support tool by integrating live EV registration data and geospatial APIs. With real-time data streams, planners can dynamically recompute demand forecasts and optimize station placement interactively. This supports agile infrastructure planning and timely policy intervention.The main conclusions are as follows:

- Based on the CEEMDAN-XGBoost time series model, this research achieved high-precision forecasting of EV ownership trends across various regions, providing reliable data support for national planning.
- The forecast suggests that Malaysia's future EV growth will remain concentrated in the western coastal economic corridor. However, other regions, particularly the east and northern states and East Malaysia, are expected to gradually catch up. Therefore, infrastructure deployment must balance long-term growth needs and prevent regional inequality.
- The current charging station network exhibits significant shortfalls, especially along major highways and underserved rural or remote areas. Accelerated deployment in these zones is essential to support long-distance travel and improve EV adoption in marginal regions.
- The proposed charging station optimization strategy identifies key transportation corridors and weak-coverage areas for prioritized deployment. These can serve as a reference for improving national service coverage and equity.

Accordingly, we recommend that government agencies adopt a data-driven, phased, and targeted investment approach for mid- to long-term charging infrastructure planning. For example, the nationally stated goal of deploying 10,000 public charging stations should prioritize the key regions identified in this study, while encouraging both public and private sector participation in deployment.

Simultaneously, supportive policy measures—such as subsidies, utility pricing reforms, and usage-based incentives—should be enhanced to ensure practical and effective implementation. A complete and accessible charging network is essential to alleviate consumer concerns, accelerate EV adoption, and contribute to Malaysia's green mobility transition.

This study provides a scientific basis for policy formulation and private sector investment. Future work will focus on extending the proposed model for real-time monitoring and policy feedback evaluation, with the goal of supporting continuous data-informed decision-making.

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# Dual Neural Paradigm: GRU-LSTM Hybrid for Precision Exchange Rate Predictions

Shamaila Butt
Faculty of Business, Sohar University, Sohar, Oman

***Abstract*—The USD/RMB exchange rate is significant when examining the structure of the Chinese financial system. Predicting the accurate USD/RMB exchange rate enables individuals to analyze the condition of the economy and prevent losses. We propose a novel hybrid approach of GRU-LSTM to improve the forecast of the future USD/RMB exchange rate. Deep learning techniques have become the cornerstone of numerous computer vision and natural language processing fields. This paper discusses various aspects and aims to show that they can help predict the exchange rate. We investigate how the newly developed hybrid GRU-LSTM model performs in terms of success rate and profitability compared with the LSTM and GRU models. The evaluation of the model is done on the USD/RMB currency pair and the forecasts made from September 13, 2023, to December 11, 2023. To increase the accuracy of the model, metrics like mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and mean absolute relative error (MAPE) were introduced. The study found that the novel hybrid GRU-LSTM model was performing relatively well compared to the models of LSTM and GRU deployed in the survey for exchange rate prediction. This improvement can significantly benefit the analyst or trader in making the right decisions on the management of risks. The study further opens new possibilities for using the hybrid GRU-LSTM model by demonstrating the enhanced potential of this method, which can be more effective in the financial environment. Subsequent studies might improve the forecast by increasing the set of hybrid models and including more economic variables.**

***Keywords*—Prediction; LSTM; GRU; USD/RMB exchange rate; deep learning**

## I. Introduction

The FOREX market is the largest market where the exchange of currencies takes place worldwide [1]. Trillions of dollars are exchanged by traders daily [2]. Since the currency prices are highly volatile, the FOREX market is referred to as a black box due to its intricacies and instabilities [3]. The authors in study [4] state that the exchange market is open 24/7. Nonetheless, the four primary time zones of Australia, Asia, Europe, and North America are used to verify the transactions. Each zone has its own hours of operation, and because it takes a lot of money to influence the exchange rate, scammers cannot easily manipulate the market [5]. Among other fields, foreign exchange market forecasting has attracted significant interest among researchers for several decades.

The international financial market is increasingly influenced by the exchange rate, a significant element affecting the global economy. Research has shown that whenever the volatility of the USD/RMB exchange rate exceeds a certain threshold, it has a negative impact on both national economic growth and the global economy. This underscores the importance of accurate USD/RMB exchange rate forecasting. The government has stated that rapid exchange rate changes intensify economic pressure, which high-precision exchange rate forecasting can help relieve. Such forecasting is not only essential for maintaining financial market stability but also aids in modifying the distribution of government resources, serving as a strong foundation for relevant administrative departments.

Moreover, deep learning has revitalized artificial neural network research. Deep neural networks (DNNs) have shown remarkable efficacy in various domains, such as computer vision and NLP. Enormous neural network optimization and control, the accessibility of extensive datasets, the computational capacity to train large networks, and approachable software libraries are associated with significant methodological advances [6]. Deep learning differs from traditional machine learning because it can independently extract discriminative features from raw data [7]. This capability reduces the need for human feature engineering while expanding the scope of deep learning applications. It also lowers the cost of deploying learning algorithms in the industry and facilitates model maintenance operations. Recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are powerful deep learning techniques. RNNs are built to handle almost any type of time series, audio, and natural language data sequences.

Deep learning-based prediction models and their financial sector applications have been the subject of recent research [8], [9]. Nonetheless, not much research has been conducted on the forex market—research is scarce in this area for a few reasons. Determining the degree of accuracy with which market developments can be anticipated is a valuable academic and practical task. Moreover, exchange rates represent a highly stochastic, nonlinear, and non-stationary financial time series [10]. As such, they are challenging to anticipate and an exciting subject for forecasting studies [11]. Finally, since the foreign exchange market differs significantly from other financial markets, research studies on different financial markets, including the stock market, may not apply to the foreign exchange market.

Numerous studies have addressed the various features of the foreign exchange market. For instance, a lot of players in the foreign exchange market are trained by professional traders [12]. The foreign currency market has a higher percentage of short-term interdealer transactions than the stock market [13], [14]. Furthermore, the considerable fluctuations in exchange rates leave traders wanting to decide what to buy or sell. As a result, the fair value model needs to be more convincing to foreign exchange traders than to traders in the stock market [15].

Although there is a need for more research on advanced deep-learning algorithms for exchange rate prediction, this

uniqueness makes it challenging to apply empirical results from other financial markets. Therefore, this study addresses critical gaps in exchange rate prediction by focusing on integrating microstructure variables such as bid-ask spread and order flow, which are often overlooked in traditional models. This approach enhances the accuracy of predictions and provides actionable insights for traders and policymakers. This study's primary objective is to add to the knowledge of exchange rate prediction by revising the deep learning algorithm for forex market dealers and reviewing the accuracy of the relevant models while predicting foreign currency movements. Given that this specificity is questioned by research on recent methods of in-depth learning to indicate the general state of other financial markets and the prediction of exchange rates, a concentrated study is encouraged. This thesis aims to retrofit the automatic learning procedure according to foreign exchange forecasts and review the accuracy of the relevant models while predicting foreign currency movements.

This study offers a novel method for predicting the USD/RMB exchange rate using microstructure variables, particularly high-frequency data at 1-minute intervals. Unlike previous studies that primarily rely on macroeconomic variables, this research pioneers the utilization of microstructure indicators—bid price, ask price, bid-ask spread, and order flow—which capture market inside information or private information inaccessible to the public. By incorporating these indicators, the model gains access to hidden or private information crucial for predicting exchange rate movements accurately. This novel approach forms the basis of research novelty and represents a significant departure from the conventional approach. To the best of the author's knowledge, no prior study had employed these microstructure and high-frequency indicators with a comparable level of granularity to predict exchange rates.

The novel approach and method employed align with the paper's goals. The primary objective of this study is to develop and validate a hybrid GRU-LSTM model that incorporates high-frequency microstructure indicators. To identify the exchange rate fluctuations, it is necessary to strengthen the internal structure of LSTM and integrate it with GRU. Then, the search conducts an empirical analysis of the given data concerning the USD/RMB exchange rate to extract helpful information like the bid price, ask price, bid-ask spread, and the flow of orders. These parameters act as dependent variables, extracting private or concealed information on the Forex market to determine exchange rates. The last objective of the study is to undertake exploratory research to evaluate the effectiveness of the proposed hybrid GRU-LSTM model against other distinct models, such as GRU and LSTM, drawn from the prediction models. All these tests will contain an analysis of the prediction errors and error margin for each of the given tests. Thus, based on the aims mentioned above, the study aims to propose a sophisticated and accurate forecasting model of the USD/RMB exchange rate. Additionally, we would like to extend our knowledge base and invest in the positive evolution of such sub-disciplines as financial modeling or other algorithmic trading.

The study's objectives are: (1) to apply microstructure indicators and optimize the internal LSTM architecture to create and calibrate the new GRU-LSTM model. Although this approach has limitations, its primary use is (2) to present selected USD/RMB exchange rate data characteristics, including bid price, ask price, bid-ask spread, and order flow. (3) to perform a research study to compare the ability of the hybrid GRU-LSTM model to the rest of the prediction models. As a result, it will be feasible to broadly assess the prediction model's accuracy and error margin. The research offers a vigorous and novel method for predicting the USD/RMB exchange rate. Additionally, the study contributes to advancements in algorithmic trading strategies and financial modeling.

The organization of the study is as follows: In Section II, relevant literature is compiled, and the paper's contribution to bridging research gaps is demonstrated. Section III discusses the empirical findings and outlines the experimental setup for the LSTM vs. GRU forecasting comparison. A summary and discussion of the results, policy implications, and opportunities for future research summarizes the paper.

## II. Related Works

Many techniques have been used to forecast the Forex market in the past few years. Many such algorithms have been tried and experimented with, but the machine learning algorithm has a higher proportion. Depending on the specific study, some will use two or more methods, while others may only include one processing method. Thus, over the past few years, several ML models have been developed and used to predict the foreign currency market. Some of the approaches used in these divisions include regression analysis, decision trees, trading rule methodologies, fuzzy logic, and support vector machines. It was necessary to develop a hybrid model consisting of the cuckoo search algorithm and regression techniques for predictive modeling [16].

The authors in study [17] and [18] applied the USD/EUR currency pair, where they built the framework of a dataset derived from the autoregressive moving average (ARMA) model. The dataset has been instructed to use the following regression methods: SVR, PLS, CRT regression tree, and multiple linear regression. The four algorithms have developed weights, and the Cuckoo search algorithm uses it in its input data. The test used the pre-test data from two years to analyze. SVR, PLS, and CRT enhance the results obtained from MLR. Regression analysis has test results that are higher than those of other models, according to them. As in study [19] noted, a statistical and predictive analysis model has been developed to simplify autoregression in compressed vectors. They reduced a considerable amount of FOREX data using a random compression technique. Afterward, each random compressed data set was loaded into the Bayesian model averaging (BMA) method to find the intersecting parameters. The currency pairs show a significant mean squared error due to a condition including four lag-dependent variables and random compression of other Forex currency pairings. Their suggested approach has worked well for the following six currency pairs: AUD/JPY, CAD/CHF, EUR/DKK, CAD/JPY, EUR/MXN, and EUR/TRY. It has also outperformed the widely used Bayesian Autoregression benchmark. Previous studies such as study [20], [21] predicted foreign currencies used a similar methodology.

Many researchers have been working on creating prediction models based on trade regulations during the last few years.

The requirements for entry, exit, and currency management are outlined in the trading regulations. These rules are essential for judging if a deal will succeed or fail. The authors in [22] presented a model for exchange rate online prediction based on rules using the weighted majority (WM) approach for expert selection. Because the technology provides continuous estimates, they needed help maintaining a decent percentage of projections. As a solution, they have considered the recommendations made by websites and made plans based on them. The mean square error and realized profit figures were used to select the website. Data analysis showed that the intersection method offers a 30% higher accuracy in the 20-day prediction than the baseline. Some researchers have applied trade rules [23], [24]. Moreover, decision tree models have not been used as frequently as other methods. Authors in [25] have created a model that produces real-time FOREX market data. After that, these data would be converted into decision tables that must be bought, sold, or retained for specific attributes. Furthermore, the CART and C4.5 algorithms assessed the categorization's quality. Three device pairs and three files from each pair were used to create the system. Most data (86–98%) belong to the queue class, which makes data processing more difficult. Examining the decision tree's dimensions and the classification accuracy, it was found that the CART method produced the best results. Additionally, the researchers in study [26] use this method.

Furthermore, support vector machines, or SVMs, were another popular statistical prediction method. SVM with prediction capability was used for both individual and hybrid systems. An SVM-based model for foreign exchange prediction was presented in study [27]. They used the EUR/USD exchange rate to put their model into practice. They divided the results into positive and negative output categories using the cross-validation approach on their data set. To compare the outcomes, they used macro and micro averaging and both positive and negative accuracy rates. With the help of the Gaussian RBF approach, they got a difference in the training and test sets as high as 29.5%. Nevertheless, the difference was rather small with a polynomial model. Therefore, the kernel function derived using polynomial has given high performance. In addition, SVM raised the profit rate threefold when analyzing SVM transactions with a conventional strategy called the transaction model. Several scholars have also applied SVM in their research [28], [29].

In recent studies, scholars expressed their concern in natural language processing (NLP). Algorithms that are based on NLP have been used in foreign exchange, as in any other industry, for predicting the exchange rates. Besides, NLP has a high level of efficiency in both the prediction function and automatization of text-based functions [30], [31].

Numerous algorithms have attracted researchers' interest, Optimization Techniques stands as one of the most recognized algorithms. According to study [32], there has been a proposal of a model incorporating the following: the extreme learning machines along with the Jaya optimization to estimate device change rates. They employed USD/INR and USD/EUR as their two currencies in those analyses. To compare, they took their model against three models supported with NN, ELM, as well as FLANN. This led them to conclude that when it comes to optimization, ELM is superior to the other mentioned algorithms such as NN, FLANN. According to assessment data of ELM DE, the number of deficient errors affected rate of MAPE assessment. As observed above, the minimum value of MAE and maximum value of ARV and Theils U were obtained by employing ELM TLBO, ELM PSO, ELM Jaya. The researchers in study [33] employed a genetic algorithm to maximize the FOREX trading strategy and a variation-based ensembling method to produce a set of helpful trading rules. Their genetic algorithm creates rules by generating notably improved outcomes compared to the extensive search. The authors in study [34] suggested an additional hybrid learning approach. Their approach, linked to ELM-Jaya and ELM, uses a mix of technical indicators, statistical data, and both to forecast the prices of the currencies on a single exchange. Other researchers have also employed optimization strategies [35], [36].

It has been noted that chaos theory has received the interest of many researchers [37]. Several factors for exchange rate forecasting of the selected countries were incorporated, of which a novel method, Multivariate Adaptive Regression Splines (MARS), based on chaos theory, was employed apart from the above [35]. To assess their strategy, three primary FX pairs; JPY/USD, GBP/USD, and EUR/USD/KYM, utilized several types of the chaos-based forecasting model. When applying the Chaos + MARS method, they provided the most accurate forecasts of these currencies. Forecasting the global financial markets, [38] proposed a type-2 fuzzy neuro-oscillatory network with chaotic intervals CIT2-FNON. The chaotic discrete-time neural oscillator, or Lee-Oscillator, is the source of the CIT2-FNON. It is made up of short-lived fuzzy input neurons that are taken out of recurrent networks. To solve the complexity problem and create a highly Type-2 Fuzzy Logic System (T2FLS) with chaotic transient fuzzy qualities, the Chaotic Type-2 Transient Fuzzy Logic (CT2TFL) was added to their model. The FOREX price has been predicted by numerous models using chaos theory [39], [40].

Pattern-based models were also widely used and popular. The authors in study [41] created a multidimensional string model for statistical forecasting. By utilizing the D2-brane to create a 2-endpoint open string model, they enhanced the 1-endpoint open string model. They demonstrated how adding object attributes often changes the predictors' statistics by modeling several time series systems with them. They used demo simulations and four distinct currency pairs to evaluate the technology. They found that string model efficiency often increases with more extraordinary string lengths. The researchers in study [19] proposed a model that uses transformed models of general DMA and dynamic model averaging (DMA) to predict the FX rate. This method examined three forex pairs: USD/JPY, USD/EUR, and USD/GBP. Thirty percent of the entire data are used for data evaluation, and seventy percent are used to train the model. They found that the four-lag autoregression model (also known as AR (4)) and the time-varying autoregression model (also known as TVP-AR (4)) with four lags produce the best prediction result for USD/JYP based on the findings of their model proposal. The parsimonious model yields positive results for the EUR/USD data set. They predicted that the models that would perform best for this prediction would be those that use a stochastic process that evolves coefficients. Consistent DMA and DMS were found. Some researchers have used similar techniques

[42], [43].

An overview of foreign exchange rate prediction was provided by study [44]. They observed eighty-two hybrid systems that were used to predict the forex rate between 1998 and 2017. They found that hybrids with artificial neural network (ANN) foundations provide higher prediction rates with greater precision and stability. The analysis shows that hybrid models have overtaken single models. The hybrid models reduce uncertainty and offer more accuracy. After examining hybrid models based on artificial intelligence, they discovered that deep learning architecture was the least effective in predicting exchanges. Even though numerous neural network-based experiments have been conducted in the last few years [45], [46], [47]. In study [48] predicted the temporal sequence of the currencies using a hybrid C-RNN approach. A convolutional neural network (CNN) and a recurrent neural network (RNN) are combined to form a C-RNN. A data-driven strategy was used to alter the coin market's characteristics. The model was compared with CNN and LSTM methods. They discovered that the C-RNN model revealed fewer errors than the LSTM and CNN-based models using the RMSE performance evaluation approach.

The authors in study [49] use a neural network and genetic algorithm to anticipate the traded equities. This approach was used to assess the EUR/USD closing values. They contrasted their suggested model with various models, including NGD, NGW, MACD, and MA. They offered two distinct methods, one with a direction and the other with a weight. They discovered that their version Weighted, which showed a profit of 111%, outperformed version Direction, which showed a profit of 56%, after carrying out all 20 full experiences. To construct another hybrid model, [50] built another hybrid model by combining a computationally efficient functional link artificial neural network (CEFLANN) for prediction with an improved shuffling frog leaping (ISFL) model. The ISFL reduced the amount of error in the system. According to the study, three different currency pairs were employed in the method: In terms of pairs, such as USD/CAD, USD/CHF, and USD/JPY. The outcomes of the system performance were evaluated using the particle optimization method and the ISFL. The outcomes indicate that both the specialized and overall figures evince the effectiveness of the suggested model over the compared two algorithms. Analyzing the statistics of the USD/CHF currency pair, it was possible to establish that its error rate fluctuated within the range of 0. 03 to 0. 04, the USD/CAD and USD/JPY currency pairs error rates differing between 0. 04 and 0. 05.

Other researchers also took a similar approach [51], [52], [53]. The authors in study [54] examined three currency pairs to find the most accurate model for predicting exchange rates: USD/EUR, JPN/USD, and USD/GBP. An investigation of the performance of several ANN algorithms was also conducted in the study. The study used backpropagation to train the model to use neural network models after optimizing and preprocessing the raw input file. To project three distinct periods: quarterly, monthly, and daily. A multilayer perceptron with a 5-10-1 structure and a single one-step prediction mode was used for each currency pair in the study.

Similarly, other authors adopted the same strategy of analysis [51], [52], [53]. In [54] the authors examined three currency pairs to find the most accurate model for predicting exchange rates: These are USD EUR, JPN/USD, and USD/GBP. Performance analysis of several ANN algorithms was also carried out in the study as well. After optimizing and pre-processing the raw input file, the peculiarity of the study involved the use of backpropagation to train the model to use neural network models. To project three distinct periods: There are quarterly, monthly, and daily record keeping methods of releasing financial information to the public. A multilayer perceptron with 5-10-1 layers and single one-step prediction mode was used for all the currency pairs in the study.

A system that can forecast financial data and be used as an agent within the A-Trader system was proposed [55]. They examined the performance of deep learning methods and neural networks. They investigated the effectiveness of neural networks and deep learning methods. Four hidden layers, each containing 78, 64, 87, and 63 neurons, were used in the study. The B&H benchmark and the MLP agent were utilized for the performance evaluation. Their findings were split up over three distinct timeframes. Their suggested system did better for the combined primary and second periods. The authors in study [56] contrasted machine learning with statistical techniques. They investigated open, closed, high, and low variables. ASTAR produced superior results for close and high variables for one and one to five days of prediction, while GA-NN produced better results for open and low variables. The outcomes differed for predictions made over a more extended period (a month). In specific, for the remaining high and open conditions, GA-NN obtained better results than ASTAR; on the other hand, SVM yielded equal average values for both models. More recently, many more NN based systems have been realized [57], [58].

Thus, the literature analysis of the predictive models of the FOREX market indicates that future research should focus on more complex deep learning structures, mainly on the interaction between the GRU and LSTM. GRU and LSTM networks are still required to be actively used for the FOREX market prediction although prior studies were carried out with conventional machine learning algorithms such as regression, decision trees, and SVM. These new architectures of deep learning offer more specific advantages in analyzing difficult patterns and temporal correlations within FOREX data, leading to better accuracy of predictions. However, these models are relatively neglected despite their abilities to enhance the prediction precision due to integration of many predictors. Basically, interpretable models for the financial market are currently a dire necessity to come up with a better understanding of the existing principle behind predictions. Another way applicable for introducing the microstructure parameters, which include ask and bid prices, bid-ask spread, and order flow as independent variables, is an additional one, which also requires further investigation of the further increase of the models' accuracy and robustness.

This FOREX market research aims to close these gaps by focusing on analyzing and comparing the deep learning architectures like GRU and LSTM models and their combinations. These architectures possess different abilities that permit researchers to note such long-term relationships and sequential patterns in FOREX that can help them gain new perceptions and possess increased accuracy in forecasting. However, despite some limitations noted previously, adapting microstructure parameters for use in forecasting models is a

plausible way of enhancing a model's realism while at the same time increasing its effectiveness in the face of real-time market data. Thus, our work can be seen to help narrow down gaps to foster better and more suitable prediction models for a FOREX market, thus aiding in the research on financial forecasting. While prior studies have explored LSTM and GRU models independently, few have systematically compared their performance against hybrid architectures. Our study bridges this gap by conducting a rigorous evaluation of the hybrid GRU-LSTM model against standalone models using multiple error metrics (MAE, MSE, RMSE, MAPE).

## III. Methods

### A. Long Short-Term Memory

In [59] researchers introduced the long-short-term memory (LSTM) model as a potential treatment to solve the gradient problem in models. LSTM has evolved into a novel neural network system that can manage sequential inputs during the last 20 years. Given that the widely used Python library Keras has the LSTM cell [60] and seems one of the most widely utilized LSTM designs in current research.

*1) The Cell state:* The cell state is a stream of data transmitted over time. The authors in [61] claim that the LSTM can memorize dependencies across time and bridge long-term delays by the cell state. The single LSTM cell contains all; however, the cell state pathway is grayed out, as depicted in Fig. 1.

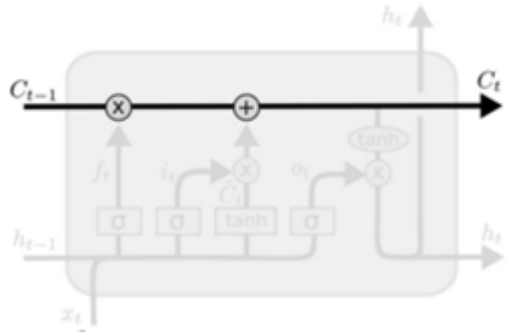


Fig. 1. The single LSTM cell contains all,; however, the cell state pathway is grayed out.

*2) Gate units:* The LSTM cell is accessible because of its several gate structures. Two inputs are typically supported by an LSTM cell: the current input $x_t$ and the recurrent input ($ht-1$, the hidden state of the previously executed time step). To read from and utilize the data contained in the cell state or to generate an updated cell state, $C_t$ gate units regulate how these inputs change the cell state. The gating processes of the LSTM cell rely heavily on the logistic sigmoid function, which can be written as expressed as $\sigma(x) = \frac{1}{1+e^{-x}}$.

It maps the recurrent and weighted current inputs to the interval $[0, 1]$. This also clarifies the meaning of the term "gate," enabling the network to control the flow of information through the gates. Values of 0 and 1 can be interpreted as allowing all information to pass through a specific gate and preventing any information from doing so. In addition to the "gatekeeper" sigmoid, two LSTM gates use the hyperbolic tangent function, that is $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$. A sigmoid gatekeeper function is used to do this, as seen in Fig. 2.

The input and output gates in LSTMs usually use the tanh activation function, which pushes inputs into the interval $[-1, 1]$. The following are the derivatives of the logistic sigmoid and the hyperbolic tangent: $d(x)\sigma(x) = \sigma(x)(1 - \sigma(x))$ and d/d(x) tanh(x) = 1 - tanh2 (x). As a result, they may be used in network training, which comes after backpropagation.

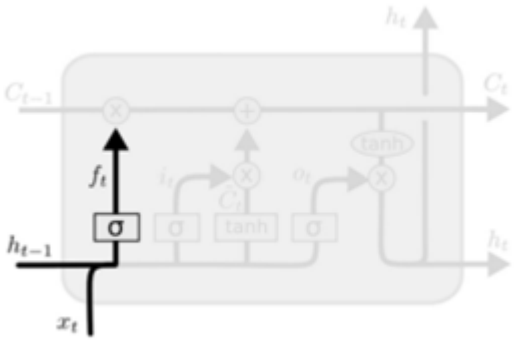


Fig. 2. Depicts the forget gate multiplied by the previous cell state $C_t - 1$ to ignore information [62].

*3) The Forget gate:* The portions of $C_t - 1$ that the cell state carried over from the previous time step are recognized and saved using the forget gate ft.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

To further enable selective retention of information in memory, it is multiplied by $C_t - 1$. When $ft = 1$ or $ft = 0$, all the data from $C_t - 1$ is retained or deleted accordingly.

*4) The Input gate:* The input gate, indicated in Fig. 3, uses a sigmoid to regulate the flow of information:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

This gate's function prevents unnecessary updates from affecting the cell state data accumulated throughout earlier time steps. As a result, new information is selectively updated into the cell state by the input gate [61]. An activation function, typically a hyperbolic tangent, generates a new set of candidate values to accomplish this. $\tilde{C}_t$:

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \tag{3}$$

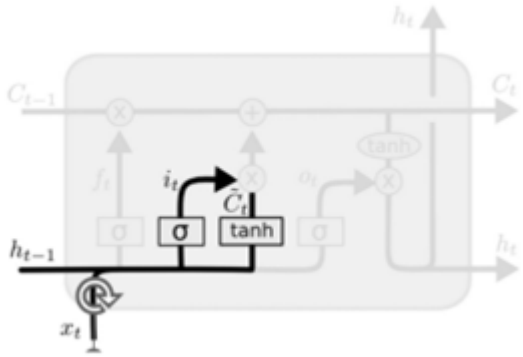


Fig. 3. The input gate 'it' directs where to update the cell state with new candidate values $C_t$ [62]

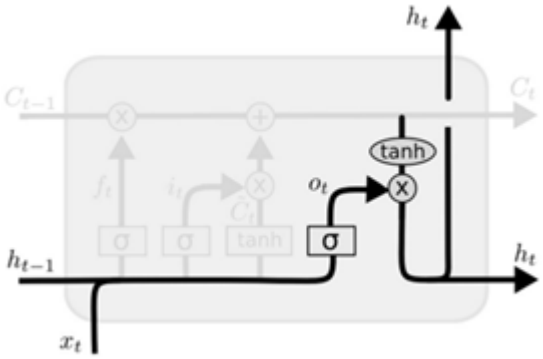


Fig. 4. The output gate 'ot' controls the network predictions [62].

*5) The Updated cell state:* The input produces the new cell state $C_t$ and forgets gate mechanisms in two stages: first, it remembers (via $f_t$) a subset of the previous cell state $C_t - 1$ and updates (via $i_t$) with the new candidate values from $\tilde{C}_t$ when necessary. At the following time step, $t+1$, this changed cell state will be received:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \tag{4}$$

Note that neither $i_t = f_t$ nor $i_t = 1 - f_t$ always holds. Not precisely the sections that were forgotten, nor the ones that were remembered, are updated. The forget gate and the input gate usually have separate weights and biases, even if they use the same arguments $(h_{t-1} and t_x)$ and an activation function of the sigmoid [62].

*6) The Output gate:* The actual prediction of LSTM depends on the current input $(x_t)$ and cell state $(C_t)$, controlled by the output gate. The current cell state data is subjected to a hyperbolic tangent, resulting in a scaled representation of the cell state within the interval $[-1, 1]$:

$$C_t^* = \tanh(C_t) \tag{5}$$

As seen in Fig. 4, the output gate $(o_t)$ uses a sigmoid with the inputs $h_{t-1}$ and $x_t$ to choose which data to send to the output layer. The time steps in the newly hidden state $(h_t)$ are then calculated.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{6}$$

The current time step's hidden output, ht, is then created by multiplying $o_t$ and $C_t^*$.

$$h_t = o_t \circ C_t^* \tag{7}$$

This output is based on the prediction at time t and the recurrent input at time $t + 1$. Predictions are calculated from the hidden state using an output activation in the last layer, just like in FNN.

*7) The LSTM cell:* Fig. 5 shows a typical LSTM cell with an input, output, and forget gate. Several gates and activations cooperate to save, hold, and produce information for the current task. When the gates and cell state are viewed as $h_t = o_t tanh(f_t C_(t-1) + i_t \tilde{C}t)$, ht can be thought of as a more complex activation function:

$$\begin{aligned} h_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \tanh\left(\sigma(W_f[h_{t-1}, x_t] + b_f) \cdot C_{t-1}\right. \\ &\quad \left. + \sigma(W_i[h_{t-1}, x_t] + b_i) \tanh(W_C[h_{t-1}, x_t] + b_C)\right) \\ &= g_h(W_h, h_{t-1}, x_t) \end{aligned} \tag{8}$$

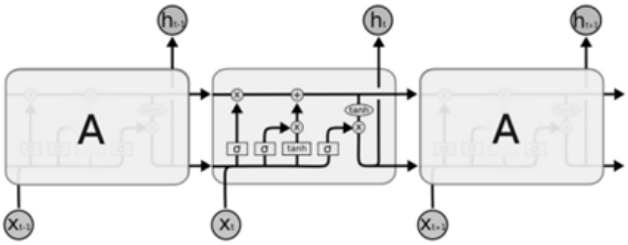


Fig. 5. A sequence of LSTM units through time [62].

This architecture, the most widely used configuration in the literature, is an improved version of the initial LSTM design. Fig. 6 shows how the cell state can transmit information over time. A series of LSTM cells are displayed throughout time. The hidden layer unit ("-" for closed and "O" for open) and the three gates to its left and above regulate which aspects of the cell state are updated, output, and forgotten at each time step.

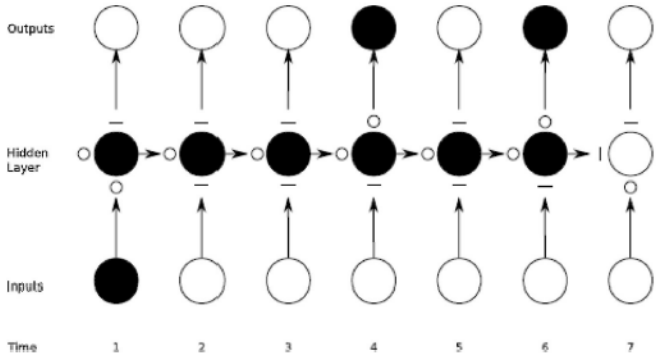


Fig. 6. Preservation of gradient information by LSTM.

### B. Gated Recurrent Units

Gated recurrent units (GRUs) are an additional method for tackling the declining gradient problem in RNNs [63]. Even though they manage the cell state more straightforwardly, they still require gates. An update gate combined an LSTM forget and input functions, but two sigmoid gates managed a GRU's hidden state.

It determines the amount of recurring data that is retained:

$$z_t = \sigma(W_z[h_{t-1}, x_t] + b_z) \tag{9}$$

A reset gate regulates the degree of hidden recurring states that can be included in the present activation.

$$r_t = \sigma(W_r[h_{t-1}, x_t] + b_r) \tag{10}$$

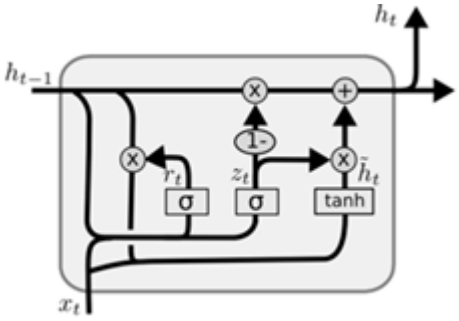


Fig. 7. Visualization of the recurrent hidden state, update gate, and reset gate over time.

Fig. 7 displays the recurrent hidden state $(h_{t-1})$, update gate $(z_t)$, reset gate $r_t)$, new hidden state $(h_t)$, and hidden state candidate vector $(h_t)$ in addition to a detailed view of the GRU cell [62]. A memory cell with a closed reset gate $(r_t = 0)$ can act as if it were reading the first observation of a sequence, overlooking the recurrent state [64]. One possible way to compute the new activation is as follows.

$$\tilde{h}_t = \tanh(W_h[r_t \cdot h_{t-1}, x_t] + b_h) \tag{11}$$

and the new hidden state is

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{12}$$

Again, the GRU cell can be thought of as an advanced activation function:

$$\begin{aligned} h_t = {} & (1 - \sigma(W_z[h_{t-1}, x_t] + b_z)) \cdot h_{t-1} + \sigma(W_z[h_{t-1}, x_t] + b_z) \\ & \tanh\left(W_h\left[\sigma(W_r[h_{t-1}, x_t] + b_r) \cdot h_{t-1}, x_t\right] + b_h\right. \\ & \left. \cdot C_{t-1} + \sigma(W_i[h_{t-1}, x_t] + b_i)\tanh(W_C[h_{t-1}, x_t] + b_C)\right) \\ & = g_h(W_h, h_{t-1}, x_t) \end{aligned} \tag{13}$$

Contrary to the LSTM, the GRU has no output activation function. Instead, the hidden cell state is constrained by the update gate, which links the input and forgets the gate. As shown in Fig. 7, GRUs contain fewer parameters than LSTMs, which should increase their computational efficiency. Regarding forecasting performance, prior research on GRUs against LSTMs is inconclusive [64], [65]. Therefore, this study focuses on both types of RNNs.

A hybrid GRU-LSTM model is shown in Fig. 8, where the input layer receives and processes the first set of data. The first hidden layer includes a pooling layer with a pool size of 1 and the same padding, a convolutional layer with 128 filters, a kernel size of 1, the ReLU activation function, and "same" padding to extract the essential features from the input. The 2nd Hidden Layer includes an LSTM layer with 128 units, depicting long-term dependencies in the data. The third hidden layer then uses the advantages of both architectures to learn complicated temporal patterns by switching between LSTM and GRU layers, each with 128 units. Finally, the output layer produces the model's predictions after processing the input data through the network's tiered structure.

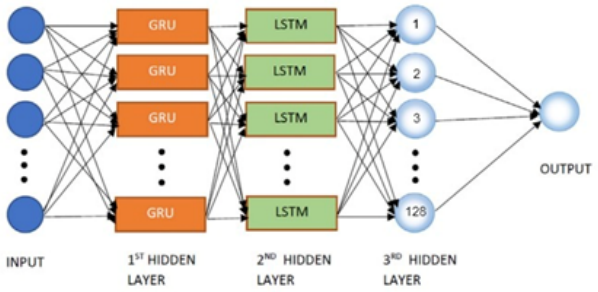


Fig. 8. Internal structure of hidden layers of hybrid model GRU-LSTM.

The flowchart shown in Fig. 9 presents the flow of the experiment, and it consists of generally arranged steps of establishing and validating a forecast model. Data collection is the first step followed by data preparation where pre-processing is completed to make the data more appropriate for training. During the pre-processing, the model is produced first, and the training data set is stored to it. This is the phase where the model for the forecast is being created; also, assessment of the model entails calculation of the loss

function. If the ending criterion is not achieved, the parameters of the model are changed, and training continues in a cycle. There is creation of the model, and when the end condition is met, then there is saving of the model. When training of the model is complete, the model is checked, and an independent testing data set is used for prediction. This is succeeded by the assessment of the performance of the model when such forecast results are prepared and analyzed. This process is to establish an appropriate forecasting mode through the loops of train and test data.

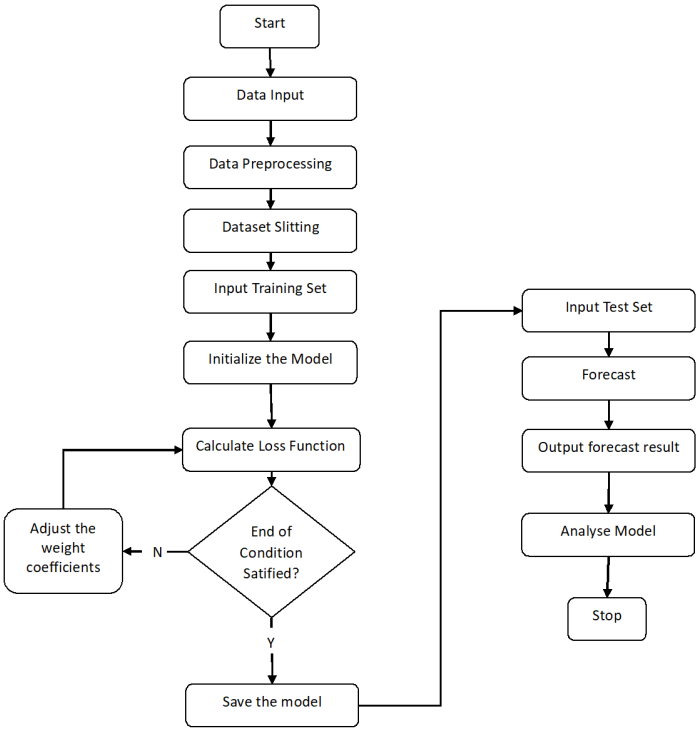


Fig. 9. Experimental process.

## IV. Experiments

This paper compares the hybrid model of the GRU-LSTM model with two individuals' models, the GRU and LSTM, to establish the efficiency of the hybrid approach. Training and the test data are identical in this case.

### A. Experimental Environment

For the trials, Google Colab version with the option of the fastest GPU: NVIDIA Tesla P100, with 16 GB of GPU memory was used. The hardware architecture of the view MPS software involved a CPU that was an Intel Xeon with 25 GB of RAM. Environment software was Python 3. 8. 10, basic machine learning libraries for instance TensorFlow 2. 8. 0, PyTorch 1. 11. 0, and Scikit-learn 1. 0. 2, and data processing and visualization applications such as Pandas 1. 4. 2, NumPy 1. 21. 5, and Matplotlib 3. 5. 1.

### B. Data Source

This paper presents a novel hybrid model for forecasting the USD/RMB exchange rate using the proposed GRU-LSTM model. The study uses the 1-minute USD/RMB exchange rate data set, which has 19807 observations. The parameters for this work are the bid price (Bid), ask price (Ask), order flow (OF), and bid-ask spread (BAS). The data was collected between September 13, 2023, and December 11, 2023.

In the forex market, the hidden daily information regarding macroeconomic fundamentals is communicated through the order flow [66]. The order flow values' sign might be both positive and negative. The sign denotes the buying and selling activity when a counterparty buys (+) at the dealer's offer or sells (-) at the dealer's bid. The Tick-test approach developed in study [67] and [68] methodology are the two main techniques used to speculate on the direction of currency transactions. Authors in study [68] compared the exchange rate and dealer quotes. Using this strategy, exchange rates higher or lower than the midpoint are classified as buy or sell. By comparing the current currency rate with the historical exchange rate, the tick-test examines fluctuations in exchange rates to determine the trade direction. A buy (uptick) is a rise in exchange rates or a transaction at a price more significant than the prior one. If not, a sell (down-tick) would be considered. At the same time, the transaction rates remain unchanged (zero-tick). According to [67], the transaction is classified according to the most recent difference between the current and exchange rates. Table I states the rules to differentiate between the buyers-initiated and the sellers-initiated trade.

TABLE I. Identification Algorithms: Tick Test

| Specification | Conjecture for trade |
|---|---|
| $S_t > S_{t-1}$ | Buyer-initiated |
| $S_t < S_{t-1}$ | Seller-initiated |
| $S_t = S_{t-1}$ | The conjecture for trade at $t$ |

Source: Adopted from [67]

The tick-test approach is used in this study because it is more accurate and adaptable [13], [12]. The order flow is calculated. Every trade is valued at $+1$ for purchases and $-1$ for sales. The daily trade is then the sum of all trade activities, whether buy or sell. Thus, researchers in [66] measure the daily order flow, defined as the buyer- and seller-initiated orders at the start of the working day. The related empirical studies used the same proxy for measuring the order flow [69], [70]. This research tracks tick-by-tick order flow one-minute data. The data is gathered from Bloomberg sources. The tick-test approach is used in this study because it is more accurate and adaptable [13], [12]. The order flow is calculated. Every trade is valued at $+1$ for purchases and $-1$ for sales. The daily trade is then the sum of all trade activities, whether buy or sell. Thus, [66] measures the daily order flow, defined as the buyer- and seller-initiated orders at the start of the working day. The related empirical studies used the same proxy for measuring the order flow [70], [69]. This research tracks tick-by-tick order flow one-minute data. The data is gathered from Bloomberg sources. The tick-test approach is used in this study because it is more accurate and adaptable [13], [12]. The order flow is calculated. Every trade is valued at $+1$ for purchases and $-1$ for sales. The daily trade is then the sum of all trade activities, whether buy or sell. Thus, [66] measures the daily order flow, defined as the buyer- and seller-initiated orders at the start of the working day. The related empirical studies used the same proxy for measuring the order flow [69], [70]. This

research tracks tick-by-tick order flow one-minute data. The data is gathered from Bloomberg sources.

The ask price, bid price, and bid-ask spread are essential factors in predicting exchange rates. The bid price (buyer price) and ask price (Sell price) data are taken from Bank of China [71]. The realized bid-ask spread and the quoted bid-ask spread are the two ways to define the bid-ask spread [72]. The average difference between the purchase and sell prices the trader quotes when the buy and sale transactions occur at different times is known as the realized bid-ask spread. Alternatively, the difference between the purchase and sell prices that the dealers quote at trade time is known as the quoted bid-ask spread, and it is determined by the quantity transacted, stock price, and number of market makers (Chen, 2012). There is a strong correlation between exchange rate risk and the bid-ask spread, according to study [70] and [12]. The bid-ask spread data is computed as the difference between the ask (sell) price and the currency rate's bid (buy) price. Table II displays a subset of the data extracted from the Table I.

TABLE II. PARTIAL SAMPLE DATA

| Date | ER | Bid | Ask | OF | BAS |
|---|---|---|---|---|---|
| 2023-09-13 01:35:00 | 7.2835 | 7.2835 | 7.2835 | 0 | 0 |
| 2023-09-13 01:36:00 | 7.2820 | 7.2820 | 7.2820 | -4 | 0 |
| 2023-09-13 01:38:00 | 7.2823 | 7.2823 | 7.2823 | 4 | 0 |
| 2023-09-13 01:39:00 | 7.2835 | 7.2835 | 7.2835 | 3 | 0 |
| 2023-09-13 01:40:00 | 7.2835 | 7.2835 | 7.2835 | 3 | 0 |

The complex nonlinear patterns of exchange rate fluctuations are too intricate to capture by traditional linear methods. Thus, researchers are adopting nonlinear methodologies that are intended to be more accurate [73], [74]. In times of economic turmoil and high volatility in the foreign currency market, when structural disruptions cause linear assumptions to be distorted, nonlinear models play a crucial role in predicting exchange rates [12].

The nonlinearities are efficiently managed by deep learning techniques such as GRU and LSTM. From September 13, 2023, to December 11, 2023, Fig. 10 illustrates the USD/RMB exchange rate for 1 minute dataset. It first displays an early appreciation of the RMB, followed by a sharp depreciation, stabilization, recovery, and a second depreciation phase. These oscillations underscore the necessity for nonlinear models to precisely forecast exchange rate movements and seize trading opportunities despite the extreme volatility and quick changes in the market. Economic data, policy changes, market sentiment, and geopolitical events impact these oscillations.

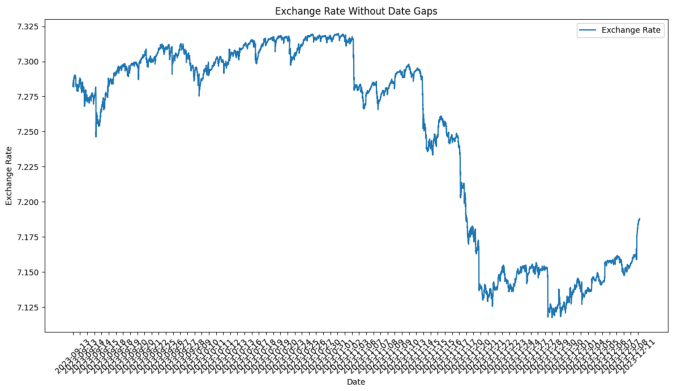


Fig. 10. Forex market dataset USD/RMB.

### C. Descriptive Statistics

Table III shows a tabular representation of the descriptive statistics provided for the parameters such as RMB/USD exchange rate (ER), bid price (BID), ask price (ASK), order flow (OF), and bid-ask spread (BAS). This table summarizes the statistical measures for parameters based on the data from 19,808 observations. The mean values for bid and ask prices are very close, indicating a tight spread, confirmed by the mean BAS value being nearly zero. The standard deviation (std) across the bid, ask, and ER is similar, suggesting that the RMB/USD pair has been trading with relatively stable volatility. The order flow's large standard deviation points to significant buying and selling activity. The minimum and maximum values indicate the range of trade, while the distribution of the values is suggested by the 25th, 50th (median), and 75th percentiles.

TABLE III. DESCRIPTIVE STATISTICS

| Statistic | Bid | Ask | ER | OF | BAS |
|---|---|---|---|---|---|
| count | 19808 | 19808 | 19808 | 19808 | 19808 |
| mean | 7.24796 | 7.24783 | 7.24787 | 0.42392 | -0.0001 |
| std | 0.0703 | 0.07035 | 0.07034 | 5.03654 | 0.00029 |
| min | 7.1175 | 7.1174 | 7.1175 | -65 | -0.0028 |
| 25% | 7.1574 | 7.1574 | 7.1574 | -3 | 0 |
| 50% | 7.2839 | 7.2837 | 7.2838 | 2 | 0 |
| 75% | 7.3045 | 7.3044 | 7.3044 | 3 | 0 |
| max | 7.3198 | 7.3198 | 7.3198 | 67 | 0 |

### D. Data Preprocessing

The data preprocessing stages for exchange rate data involved several fundamental data transformations in preparing the data for a model. First, we converted the date column into a date-time format to assign it as the index and facilitate time series analysis. After that, the data was reset so that the date would appear as a column for further processing. To maintain chronological order, the dataset was sorted using dates to determine the ascending order.

Descriptive statistics were then produced to provide an overview of the dataset. "ER" was the target variable, and "Bid," "Ask," "OF," and "BAS" were the features chosen for the model. The features and the target variable were normalized using the MinMaxScaler to scale the values between 0 and 1 to 1 to improve the performance of models. Then, we established data sequences with a defined length of 4,

meaning each sequence had four data points in a row. The target value for each sequence was the data point that came just after the sequence. The scaled data had to be iterated over to create sequences and their corresponding targets. The resulting sequences were then transformed into numpy arrays. Ultimately, the data was separated into training and testing sets. After training 80% of the data, the model was evaluated on 20% using an 80:20 split ratio. The model was trained on most of the data for this split, and its performance was assessed using an unknown component.

### *E. Experimental Parameter Settings*

The critical parameter choices for a neural network model with convolutional and LSTM/GRU layers intended for sequential data analysis are shown in Table IV. Convolutional layers are set up with 128 filters, each using a ReLU activation function and a 1 x 1 kernel size to extract features while introducing nonlinearity effectively. Both convolutional and pooling layers utilize padding to maintain input/output dimensions. The LSTM/GRU layers are set to contain 128 hidden units, employing a Tanh activation function to capture temporal dependencies effectively. With a learning rate of 0.0001, the Adam optimizer improves the model, which guarantees adaptive changes to the weight parameters during training. Multiple loss functions, including MAE, MSE, RMSE, MSLE, Median Absolute Error, and MAPE, are employed to evaluate model performance from different perspectives. In any training, epochs are several complete cycles through the entire data set, and batch size is the number of training instances processed at each pass, therefore, training is performed over 50 epochs with a batch size of 54, which helps in optimizing the model for working on sequential data tasks. The purpose of such an elaborate set of parameters is to examine the sequential data, along with good performance and stability.

TABLE IV. MODEL PARAMETER SETTINGS

| Parameters | Value |
|---|---|
| Convolution layer Filters | 128 |
| Convolution layer Kernel Size | 1 |
| Convolution layer Activation Function | ReLU |
| Convolution layer padding | Same |
| Pooling layer pool size | 1 |
| Pooling layer padding | Same |
| LSTM-GRU Hidden Units | 128 |
| LSTM-GRU Activation Function | Tanh |
| LSTM-GRU Optimizer | Adam |
| LSTM-GRU Learning Rate | 0.0001 |
| LSTM-GRU Loss Function | MAE, MAP, RMSE, MedAE, MAPE |
| LSTM-GRU Epochs | 50 |
| LSTM-GRU Batch Size | 54 |

Note: The table shows the ideal parameters for each GRU-LSTM model layer. The acronyms MAE, MAP, RMSE, MedAE, and MAPE stand for Mean Absolute Error, Mean Average Precision, Root Mean Squared Error, Median Absolute Error, and Mean Absolute Percentage Error, respectively.

### *F. Experimental Results and Analysis*

The primary objective of this study is to forecast the USD/RMB exchange rate with three different models' levels of accuracy: a hybrid GRU-LSTM model, a Gated Recurrent Unit (GRU), and a Long Short-Term Memory (LSTM) model. Various assessment criteria are used to assess these models, including training duration, MAE, MAP, RMSE, MAE, and MAPE. Before training, the dataset is standardized. Every model project the closing price for the subsequent trading day; the expected and actual values are then contrasted. A standardized Forex dataset is used in the studies for both evaluation and training. The LSTM, GRU, and hybrid GRU-LSTM models are trained on this dataset to forecast the closing values of the USD/RMB exchange rate. The model's parameters are adjusted to lower error metrics while the data is processed throughout several epochs during training.

Fig. 11 displays the performance of the LSTM model over ten epochs. The x-axis shows the epochs, while the y-axis displays the loss values. Included in the metrics are validation loss (Val-loss), training loss (Train-loss), mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE). All metrics demonstrate a decreasing trend, indicating effective learning and improved predictions. The rapid initial decline in error values reflects the model's quick adaptation to data patterns. Despite minor fluctuations, the steady decrease in training loss and the general downward trend in validation loss suggest effective learning with some overfitting. The consistent decline in MSE, RMSE, and MAE confirms enhanced prediction accuracy.

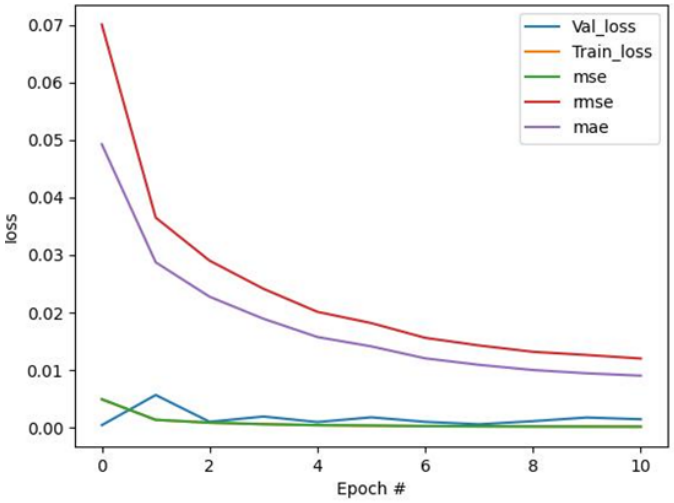


Fig. 11. LSTM Training and Validation loss for selected evaluation metrics.

Fig. 12 illustrates the performance of the GRU model over the same period. Like LSTM, the GRU model exhibits a rapid initial decline in error metrics, indicating efficient learning. The GRU model converges faster and displays stable validation performance with fewer fluctuations, indicating more consistent generalization. Both models effectively reduce errors and enhance predictive accuracy, with the GRU model demonstrating slightly faster and more stable convergence.

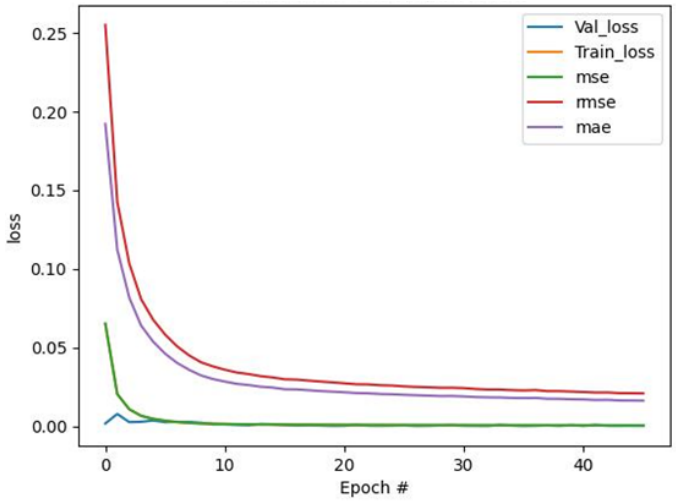


Fig. 12. Loss function for the training and validation for selected evaluation metrics.

The loss function for the combined LSTM and GRU model is shown in Fig. 13. To improve forecasting accuracy, the hybrid GRU-LSTM model combines the best features of the LSTM and GRU architectures. LSTM networks excel at learning long-term dependencies with their robust cell state and gate mechanisms, while GRUs offer computational efficiency and effective handling of short-term dependencies. In the hybrid model, data first passes through an LSTM layer to capture long-term patterns, then through a GRU layer to efficiently capture additional short-term patterns. This combination improves overall predictive performance, as demonstrated by the close alignment of the hybrid model's predictions with actual exchange rates in the provided plots. Since the hybrid model can account for both short-term volatility and long-term trends, it is a reliable method for forecasting the USD/RMB exchange rate.

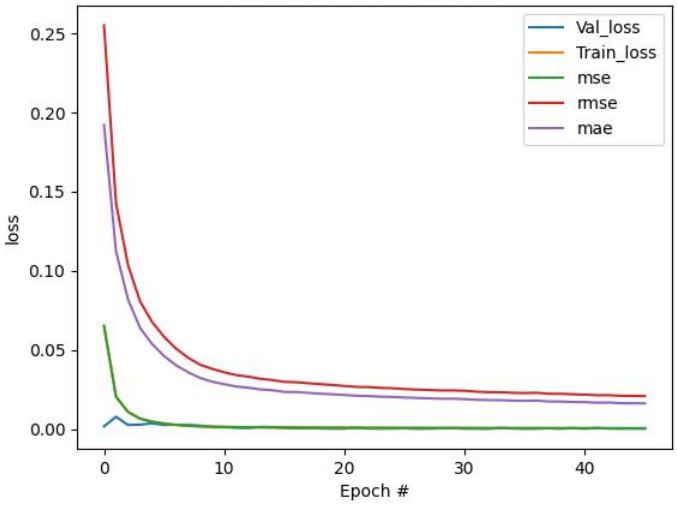


Fig. 13. The Loss function of the hybrid model for the training and validation of selected evaluation metrics.

The error metrics for the LSTM and GRU models trained on a Forex dataset. Both models exhibit a rapid initial decline in metrics such as training loss, validation loss, MSE, RMSE, and MAE, indicating efficient learning. The LSTM model shows steady improvement with minor fluctuations in validation loss, suggesting some variability in generalization. In contrast, the GRU model exhibits more consistent generalization due to its faster convergence and stable validation performance with fewer fluctuations. While both models can reduce errors and improve prediction accuracy, the GRU model shows quicker and more consistent convergence.

The prediction of the LSTM model is shown in Fig. 14, where it demonstrates an excellent predictive capability but is less consistent than the hybrid GRU-LSTM model, particularly during times of high volatility. Although some overfitting is seen because of small changes in validation loss, the model learns efficiently, as evidenced by the consistent decrease in training and validation loss. The model's predictions get more accurate with time, as evidenced by the steady drop in the MSE, RMSE, and MAE metrics.

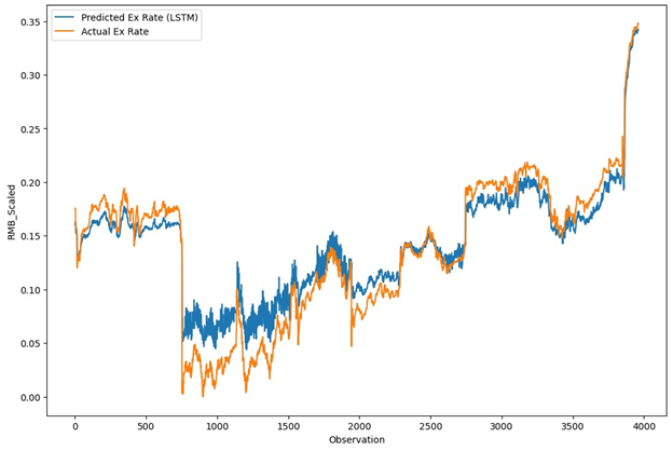


Fig. 14. LSTM Model's prediction for the test dataset.

The GRU model performs better than the LSTM model in terms of validation performance stability and convergence rate, as shown in Fig. 15. The validation loss fluctuating less suggests better generalization to unobserved data. Because of its strength, the GRU model is suitable for time series forecasting tasks where dependable performance is crucial.

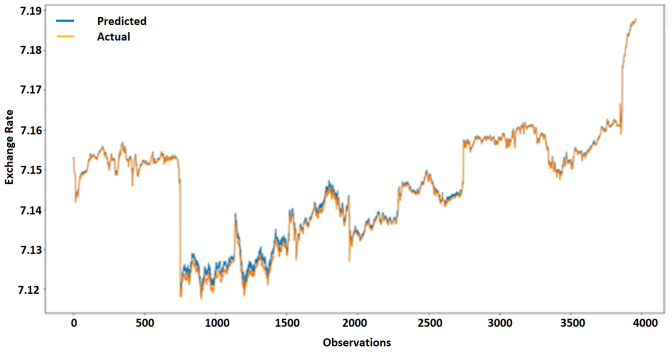


Fig. 15. GRU Model prediction for the test dataset.

Fig. 16 demonstrates how a hybrid GRU-LSTM model better captures short—and long-term trends and fluctuations compared to the LSTM or GRU individual model. The hybrid model is a more accurate and reliable forecasting tool since it can use both architectures. This model closely aligns predicted values with actual exchange rates, demonstrating its robustness in handling financial time series data complexities. A high degree of accuracy is indicated by slight differences between expected and actual values; only occasional anomalies impact predictions.

The evaluation metrics of the GRU, LSTM, and hybrid GRU-LSTM models are displayed in Table V. The Mean Absolute Error (MAE) of 0.003368 indicates the average deviation from actual values for the Long Short-Term Memory (LSTM) model, created to represent long-term dependencies in sequence data. Its Root Mean Squared Error (RMSE) of 0.004109 indicates the impact of sporadic, more significant inconsistencies, even though its Mean Squared Error (MSE) of 0.000017 is relatively minor. The Mean Squared Logarithmic Error (MSLE) is zero, indicating robustness in handling logarithmic differences. The percentage accuracy is indicated by the Mean Absolute Percentage Error (MAPE) of 0.0472%, and resilience to outliers is indicated by the median absolute error of 0.002902.

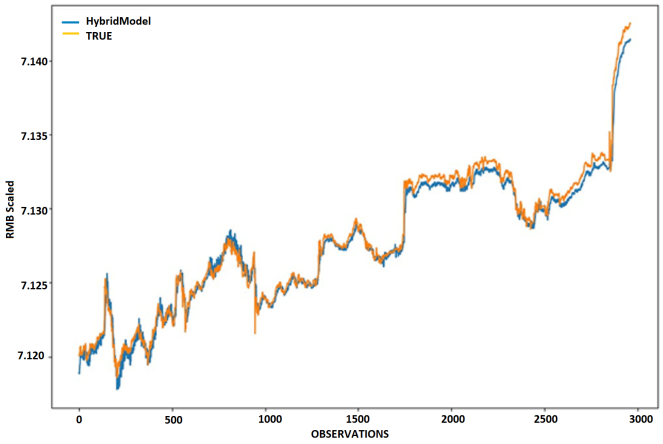


Fig. 16. Hybrid Model's prediction for the test dataset.

TABLE V. EVALUATION MATRICES

| Model | MAE | RMSE | MedAE | MAPE |
|---|---|---|---|---|
| GRU-LSTM [75] | 0.0012 | 0.0015 | N/A | 0.0010 |
| LSTM [76] | 0.0025 | 0.0032 | N/A | 0.0021 |
| GRU [77] | 0.0018 | 0.0023 | N/A | 0.0015 |
| LSTM | 0.0033 | 0.0041 | 0.0029 | 0.0004 |
| GRU | 0.0025 | 0.0037 | 0.0013 | 0.0004 |
| Hybrid GRU-LSTM | 0.0004 | 0.0005 | 0.0003 | 0.00006 |

The GRU model outperforms the LSTM in all criteria while maintaining similar functionality and simplifying the LSTM architecture. The MAE of 0.002505 indicates increased accuracy, with average predictions closer to actual values. A reduced error size is marked by an RMSE of 0.003746, highlighting improved overall prediction performance. A more consistent error distribution is indicated by the median absolute error of 0.001261, indicating that outliers impact the GRU less. The GRU model exhibits better accuracy than the LSTM model, with an average percentage error of 0.0351%, indicating a small average percentage error.

## V. DISCUSSION

The findings of this study have significant implications for both practitioners and researchers. The hybrid GRU-LSTM model offers traders a reliable tool for predicting exchange rate movements, enabling them to manage risks more effectively. For researchers, the integration of microstructure variables highlights the importance of leveraging high-frequency data to uncover hidden patterns in financial markets. Moving forward, future studies could explore the application of hybrid models in other financial domains, such as stock price prediction or commodity trading.

The hybrid GRU-LSTM model outperforms the LSTM model on all evaluation measures by combining the best aspects of the GRU and LSTM architectures. The predictions of the hybrid model are surprisingly close to the actual values, with an MAE of only 0.000433. The model's outstanding performance is further supported by its RMSE of 0.000565, which shows the lowest error magnitude among the models. The lowest median absolute error, 0.000380, indicates that the model's predictions are less affected by anomalies and are, hence, stable. Finally, the hybrid model yields the most accurate and trustworthy forecasts, as evidenced by the MAPE of 0.0061%, the lowest average percentage deviation.

The comparison demonstrates that the GRU-LSTM hybrid model is the most accurate and consistent of the three models, surpassing the other two in each evaluated criterion. The GRU model outperforms the LSTM in all areas, demonstrating its accuracy and efficiency. Although the LSTM model performs well, the hybrid and GRU models outperform it. By utilizing the complementary advantages of both the LSTM and GRU architectures, the GRU-LSTM hybrid is the optimal option for attaining the highest prediction accuracy and consistency levels. This improved accuracy and dependability is essential when it comes to financial analysts and traders making well-informed decisions in the currency market.

The hybrid GRU-LSTM model not only improves predictive accuracy but also offers practical benefits for traders and financial analysts. By capturing both short-term volatility and long-term trends, the model enables more informed decision-making, particularly in high-stakes environments like the USD/RMB exchange market.

## VI. CONCLUSION

This research aims to establish the reliability of the novel hybrid GRU-LSTM model to predict the USD/RMB exchange rate, which is extremely valuable in the Chinese financial sector. It will also help avoid possible financial risks associated with the exchange rate while providing critical economic information. Before developing a new hybrid GRU-LSTM network architecture, the goal is to combine the characteristics of the two GRU and LSTM models to increase the model's predictive capacity. Therefore, the study outlined the research's high efficiency based on the proposed novel hybrid model and the results of using separate LSTM and GRU models for the USD/RMB exchange rate prediction.

The findings demonstrated how the hybrid model, which combines LSTM and GRU components, can be distinguished from the precise prediction accuracy of the two models with a greater variety of parameter configurations. This is basically due to its cell state and gate mechanisms; LSTM has a mighty reliable cell state; GRUs, on the other hand, are efficient and effectively assert short-term dependency connections. When one works under the hybrid model, the actual data is well managed as it has short-term characteristics by going through a GRU layer once it has passed through an LSTM layer, which handles the features of long-term patterns.

The predictive plots presented demonstrate how this sort of combination enhances overall predictive accuracy by closely replicating the actual exchange rates among other techniques in the hybrid model. The hybrid model has the significant benefit of providing analysis over both the short and long terms; as a result, it may be used to forecast the USD/RMB exchange rate. This led to improved accuracy analysis, which is vital for traders and financial analysts before making any decisions in the foreign exchange market. Thus, although the presented LSTM-based model exhibits a high level of predictability, its capability becomes relatively volatile at extreme levels of volatility. In contrast, the GRU model has a similar training performance for different epochs with less fluctuation in the validation performance and takes fewer epochs to converge. Lastly, the hybrid model, which solely captures the short-term and extended-term changes, achieves the highest predicted accuracy given by the equation of the superiority of LSTM over GRU and vice versa.

### A. Policy Implications

The study's findings have several policy implications.

- The newly proposed GRU-LSTM model provides numerous benefits to financial institutions and policy-making bodies in the projection of exchange rates by improving the model's expandability while maintaining the needed degrees of instability to account for long-term dependencies. This concept indicates that institutions can reduce currency risk by effectively employing hedging mechanisms and risk management structures that are less vulnerable. This helps avoid unfavorable currency movements, which result in declining performance on the economic portfolios, stabilizing the overall performance.
- In keeping the market stable, prompt and accurate forecasting models such as the hybrid model GRU-LSTM are vital as they highlight the exchange rate volatility. The market volatility is seen before it reaches extreme levels, which means that the financial institutions and the policymakers can respond as soon as the signs of volatility become apparent by using available instruments like the regulation of the monetary supply or using forex reserves. It acts as a shield that minimizes the disruption that comes about due to a sharp fluctuation in exchange rates, thereby minimizing shocks to financial markets, investors' confidence, and the sustainability of economic growth.
- The hybrid forecasting models' performances are highly relevant in determining policy decisions, especially in controlling foreign exchanges and monetary policies. The hybrid predictive model can be valuable for strategic planning of the economy and advantageous because it effectively facilitates anticipation of future market trends as influenced by exchange rate predictions. The projections by the predictive model facilitate the management of the monetary policies and foreign exchange reserves, thus helping counter-economic volatility and adopting stability as well as growth. Therefore, policymakers rely on predictive models when making decisions, reducing uncertainty and creating a favorable environment for the economy's long-run growth.
- The results also indicate that using deep learning improves the required models and introducing them into financial markets is the next step to achieving innovation. Financial organizations are in a diverse position to embrace innovation in their operations to enhance the viability and effectiveness of the financial services delivery systems. The models particularly excel in handling large volumes of data and more extensive and intricate patterns, thus enabling accurate prediction and decision-making. Hence, the use of advanced technology leads financial institutions to achieve a competitive market position and, at the same time, makes financial institutions more responsive to the prevailing conditions. Such flexibility enhances the financial system's effectiveness with a stressed and improved capacity to adapt to adversity and change and boosts the sector's resilience, efficiency, and innovation
- A microstructure model that integrates order flow, bid price, ask price, and the bid-ask spread is quite complex in Forex trading. However, when used, it can offer deep insights into the market that are not provided with traditional models. Essentially, through processing such data, the model predicts future variations of the RMB/USD exchange rate so that trading players can devise informed trading policies. Real-time data are easily interpreted to make it a source of trading signals that are key in responding quickly to market changes. For example, when the model indicates that the RMB is likely to appreciate against the USD, the trader may find it valuable to open a long position.
- The model also provides predictions and relative probabilities for preparing to manage risks. Trading professionals can employ these projections to place stop-loss orders and hence manage the capital that one is willing to risk per trade, not forgetting the profit targets. Probability forecasts allow traders to accurately reposition according to short-term fluctuations and long-term trends to effectively get the right timing for entering or exiting the market to earn the best profits.
- Several parameters affect placing an order, such as bid ask spread and order flow, which creates the opportunity to form positive order limits, making profit expectations high. The model outcome can also be carried out in the algorithms for actual trading since its

applicability is relevant, especially in high-frequency trading. The model's value is attributed mainly to the realization that you can obtain the probability outcomes from the model, which can then best be used in conjunction with sentiment analysis for the clients and the broker or dealers to determine the best time for trading. The traders that received this information have continued to be relevant through functional communication strategies such as swift notifications in the messaging and trading platform.

### B. Future Recommendations

Future research could consider other hybrid models or the use of ensembles for better precision in forecasting exchange rates. Also, further development of the model with more elaborate deep learning techniques, such as attention techniques, and including external economic parameters, can be helpful.

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# AI-Driven Resource Allocation in Edge-Fog Computing: Leveraging Digital Twins for Efficient Healthcare Systems

Use Case: Cardiovascular Diseases in Mauritania

Brahim Ould Cheikh Mohamed Nouh[1], Rafika Brahmi[2], Sidi Cheikh[3]*,
Ridha Ejbali[4], Mohamedade Farouk Nanne[5]
Research Unit. CSIDS of FST, University of Nouakchott, Nouakchott, Mauritania[1,3,5]
Research Unit. (RTIM), National School of Engineers, University of Gabes, Gabes 6029, Tunisia[2,4]

***Abstract*—The evolution of healthcare, driven by remote monitoring and connected devices, is transforming medical service delivery. Digital twins, virtual replicas of patients, enable continuous monitoring and predictive analysis. However, the rapid growth of real-time health data presents major challenges in resource allocation and processing, especially in cardiac event prediction scenarios. This paper proposes an artificial intelligence-based approach to optimize resource allocation in a fog-edge computing environment, with a focus on Mauritania. The system integrates a deep learning model (CNN-BiLSTM), which achieves 98% accuracy in predicting cardiovascular risks from physiological signals, combined with a Deep Q-Network (DQN) to dynamically decide whether tasks should run at the edge or in the fog. Using IoT sensors, real-time health data is collected and processed intelligently, ensuring low latency and rapid response. Digital twins provide a synchronized virtual representation of the physical system for real-time supervision. This architecture improves resource utilization, reduces processing delays, and enhances responsiveness to critical medical conditions, supporting more accurate cardiac event prediction and timely intervention, especially in resource-constrained environments.**

***Keywords*—Edge computing; fog computing; digital twin; deep learning; CNN-BiLSTM; Deep Q-Network (DQN); resource allocation; cardiac event prediction; healthcare; Artificial Intelligence (AI); Internet of Things (IoT); real-time**

## I. Introduction

Cardiovascular diseases, which claim millions of lives each year, remain one of the leading causes of mortality worldwide [1]. In Mauritania, the prevalence of cardiovascular disease (CVD) mortality is estimated at 16%, making it the leading cause of death from non-communicable diseases (NCDs) [2]. Hypertension (HTN), affecting 27% of the Mauritanian population [3], is the primary contributor to the burden of strokes, ischemic heart diseases, and hypertensive cardiopathies. The prevention, detection, and treatment of hypertension remain insufficient due to a lack of public awareness about risk factors, symptoms, and complications of the disease, as well as weaknesses in the healthcare system [4]. Implementing a decision support system [5] that facilitates early detection, alongside efficient resource management and rapid intervention in cardiac emergencies is crucial to improving patient survival rates [6] and achieve the target of a 33% reduction in premature mortality by 2030 [7].Moreover, a survey conducted among cardiologists at the National Cardiology Center (CNC) reveals strong support for these innovative solutions [8].However, the effective management of real-time data from medical monitoring devices remains a significant challenge, particularly in distributed environments (Edge or Fog Computing) where computational resources are often limited [9]. Edge-Fog Computing environments, positioned near IoT devices, allow for decentralized data processing, thus reducing latency and bottlenecks associated with data transfer to the cloud [10]. Optimizing resource allocation in such distributed systems is a central challenge. Dynamic resource management—including bandwidth, computing power, and storage—is crucial, especially when handling critical real-time data streams, such as those generated by biometric sensors and cameras in cardiac monitoring systems [11]. To address these challenges, integrating Edge-Fog Computing systems with artificial intelligence (AI) approaches and digital twins paves the way for intelligent and scalable healthcare systems that can adapt to the dynamic needs of patients and infrastructure [12] [13]. In this context, our work proposes an innovative approach to optimizing resource allocation in Edge-Fog Computing environments, specifically designed to enhance the prediction of cardiac events. It combines advanced AI models, including a hybrid CNN-LSTM model for cardiac event prediction and a Deep Q-Network (DQN) for dynamic resource allocation. This system aims to establish a real-time health monitoring framework capable of predicting patients' cardiac health status, determining the optimal location for task processing—whether at the edge or fog—and delivering rapid responses in critical situations. Moreover, integrating digital twins into this architecture enables comprehensive system supervision, providing a platform for real-time monitoring and predictive analysis [14]. These digital twins not only simulate system behavior under varying conditions [fdgth] but also continuously optimize resource allocation decisions [15]. Preliminary results indicate that this approach effectively handles workload variations, improves system performance, and supports rapid response to critical situations. The main contributions of our research study are as follows:

*1) AI-Driven heart attack risk prediction at the edge:* Development and implementation of a CNN-BiLSTM deep

*Corresponding authors.

learning model for heart attack prediction, enabling real-time monitoring and accurate risk assessment directly on edge devices.

*2) Dynamic resource allocation optimisation:* Implementation of a reinforcement learning Deep Q-Network (DQN) model to optimise resource management. This model dynamically determines whether data, including video streams in critical situations, should be processed locally on edge devices or offloaded to the fog layer in resource-intensive scenarios.

*3) Integrating digital twin technology:* Use of digital twins for cardiac monitoring in healthcare to refine the accuracy of heart attack predictions, optimise resource allocation and improve system performance through real-time monitoring, notification in critical situations and continuous optimisation based on replicated data.

The rest of this paper is organized as follows: Section II discusses related work. In Section III, we presents the proposed framework. Furthermore, Section IV is the results and discussion. The conclusion and the paper's potential future directions are presented in Section V.

## II. Related Work

Many authors have carried out studies relevant to our research. In this section, the key studies are organized into sub-paragraphs with clear headings for improved readability and are summarized below:

### A. Resource Allocation in Fog and Edge Computing for Healthcare

Talaat et al. [16] introduced EPRAM, a method combining Deep Reinforcement Learning (DRL) and Probabilistic Neural Networks (PNN) to enhance resource allocation and heart disease prediction in Fog environments. The system includes modules for data preprocessing, resource allocation, and effective prediction, significantly reducing latency and improving load balancing. Aazam et al. [17] focused on task offloading in Edge Computing using machine learning (ML) models such as kNN, Naive Bayes, and SVC. Although their models improved processing efficiency in medical scenarios (including COVID-19-related cases), they did not report specific performance metrics. Khan et al. [18] proposed a dynamic resource allocation algorithm for IoHT applications. Their results demonstrated a 45% reduction in delay, 37% reduction in energy consumption, and 25% reduction in bandwidth usage compared to existing approaches.

### B. Machine Learning-Based Medical Data Processing

Amzil et al. [19] developed ML-MDS, a medical data segmentation method that achieved 92% accuracy while reducing latency by 56%. Similarly, Ullah et al. [20] used fuzzy reinforcement learning to design energy-efficient healthcare IoT systems. Hanumantharaju et al. [21] applied Random Forest and Naive Bayes algorithms for heart disease prediction. Scrugli et al. [22], on the other hand, achieved over 97% accuracy using a CNN to detect arrhythmia disorders.

### C. Deep Learning and Synthetic Data for Cardiac Events

Rajapaksha et al.[23] used LSTM models with synthetic data to predict cardiac arrests, achieving 96% accuracy. Tang et al.[24] introduced SH-CSO, an optimization algorithm that achieved 96. 16% precision for heart disease and 97. 26% for the diagnosis of diabetes. Dritsas et al.[25] compared several deep learning models on a heart attack prediction dataset. Their hybrid model outperformed others with 91% accuracy, 89% precision, and 90% recall.

### D. Hybrid Deep Learning Models for Cardiac Prediction

Hossain et al.[26] used a hybrid CNN-LSTM model, achieving up to 74.15% accuracy. Sudha et al.[27] achieved 89% using a similar approach. Verma et al.[28] proposed the FETCH system, which combines Fog Computing, IoT, and DL to enhance real-time cardiac monitoring. Elsayed et al.[29] integrated CNN and Fog Computing for image-based diagnosis, achieving near-perfect accuracy (99.88%) on X-ray images.

### E. Architectures and Comparative Studies

Tripathy et al. [30] proposed an architecture combining quartet deep learning and edge devices, evaluated using the FogBus framework based on performance indicators such as congestion and accuracy. Scrugli et al.[22] compared several ML algorithms (LR, SVM, NB, KNN, RF, GB) to identify the best one for early heart failure detection, especially within cloud computing environments. The Table I provides an overview of studies focusing on edge–fog systems in the healthcare domain.

The Table [I] provides an overview of studies focusing on Edge–Fog systems in the healthcare domain, highlighting the key limitations identified in each study.

## III. Proposed Framework

We proposed a multi-layered framework for remote healthcare monitoring and resource allocation, including IoT sensors, edge computing, fog and digital twin technology, to predict heart attacks in real time and allocate resources efficiently. IoT sensors collect key physiological data, including parameters such as heart rate, type of chest pain and cholesterol levels, alongside video input from a camera during critical events. Edge devices are used to run pre-trained deep learning models to predict a heart attack, and activate the camera as needed. During the same time, a deep Q-Network (DQN) decides if the data is processed locally or offloaded to the fog layer. Predictions and video frames are transmitted to a digital twin, which not only monitors the patient's health but also diagnoses the situation based on the collected data. If the digital twin detects an emergency, such as a potential heart attack, it automatically notifies the medical staff, family members, and ambulance teams, enabling prompt intervention and refines resource allocation through historical analysis. Fig. 1 illustrates the architecture of this system, highlighting the seamless flow from data collection to decision making.In the following sections, each layer of the proposed architecture will be detailed in the following sections.

TABLE I. OVERVIEW OF STUDIES FOCUSING ON EDGE-FOG SYSTEMS FOR HEALTHCARE

| Reference | Focus | AI Technique / Architecture | Limitations |
|---|---|---|---|
| (Aazam et al.) [2021] [17] | underscores the significance of intelligent decision-making in resource-constrained environments for enhancing | kNN,naive Bayes (NB), SVC/ Edge-Cloud | Algorithmic Limitations : The study does not fully address how resource allocation is managed dynamically across middleware entities |
| (scrugli et al.) [2021] [22] | explore the implementation of a system for at-the-edge cognitive processing of ECG data. | CNN/ Edge-Cloud | Limited Scope of Generalization, |
| (khan et al.) [2022][18] | This paper proposes workload-aware efficient resource allocation and load balancing in the fog-computing environment for the IoHT. | algo/fog-Cloud | Overemphasis on Simulation: The study is largely validated through simulations, which might not fully replicate the complexity of real-world healthcare scenarios. |
| (talaat et al.) [2022][16] | the EPRAM paper significantly advances the understanding and implementation of resource allocation and prediction in fog computing, particularly for smart healthcare systems, by introducing a comprehensive and effective methodology. | PNN,RL/ Fog-Cloud | it lacked specific implementation details. to confirm its effectiveness in real-world healthcare FC deployments. |
| (verma et al.) [2022][28] | combines fog computing with IoT and deep learning to enable efficient healthcare monitoring and diagnosis | Random Forests, Gradient Boosting/Fog-Cloud | does not address dynamic resource allocation strategies effectively. |
| (elhadad et al.) [2022][31] | Immediate notification handling in healthcare monitoring | Algorithmic Pattern Recognition/Fog-Cloud | lacks comprehensive strategies for managing limited computational and energy resources on fog nodes effectively. This could hinder scalability for high-demand healthcare applications |
| (hanumantharaju et al.) [2022][21] | develop a novel fog-based healthcare system for Mechanized Diagnosis of Heart Diseases using ML algorithms | Random Forest, Naive Bayes/Fog-Cloud | -Dynamic Resource Allocation: The dynamic and often unpredictable nature of healthcare demands is not fully accounted for, which could lead to inefficiencies in resource utilization during peak usage periods. -Lack of Real-World Validation |
| (hossain et al.) [2023][26] | Combined CNN and LSTM to identify Cardiovascular disease | CNN, LSTM | Lack of Real-Time Deployment Considerations Neglect of Resource Allocation |
| (sudha et al.) [2023][27] | Combined CNN and LSTM to identify Cardiovascular disease | CNN, LSTM | Deployment challenges include optimizing resources in real-time environments. |
| (elsayed et al.) [2023][29] | intersection of fog computing and modified CNNs in the domain of healthcare image analysis | CNN/Fog-Cloud | Resource Constraints in Fog Computing and need to implement an effective resource allocation strategy |
| (tripathy et al.) [2023][30] | The approach uses a quartet deep learning framework combined with fog and edge computing to process healthcare data closer to the user, reducing dependency on cloud services. | DQN/Fog-Cloud | The paper emphasizes the efficiency of the fog platform but does not delve deeply into adaptive resource allocation strategies. |
| (rajapaksha et al.) [2023][23] | developed predictive model in identifying the likelihood of developing cardiac | LSTM | Lack of Real-Time Testing |
| (ullah et al.) [2024][20] | Treduce delays in processing and transmitting healthcare data | FIS,RL,NN/Fog-Cloud | Problem of dynamic resource allocation |
| (dritsas et al.) [2024][25] | apply and compare the performance of five well-known Deep Learning (DL) models, to a heart attack prediction dataset. | MLP,CNN,RNN,LSTM, GRU | Computational Overhead: hybrid architectures, are computationally intensive. how these models can be deployed in resource-constrained environments, such as edge or fog computing. |
| (tang et al.) [2024][24] | create a model for detecting diabetes and cardiovascular diseases by integrating AI and IoT | SH-CSO algorithm/Fog-Cloud | The aspect of resource allocation is not addressed, especially given that fog nodes are limited in resources. |
| (dayana et al.) [2024][32] | The paper emphasizes the importance of ML methods for early detection, diagnosis, and prevention, aiming to reduce mortality rates and healthcare costs associated with heart disease | LR,SVM,NB,KNN,RF,GB | The paper does not adequately address the practical limitations of deploying cloud-driven machine learning models in environments with limited resources |
| (amzil et al.) [2024][19] | an ML-based approach to improve health data classification and reduce latency in healthcare systems | k-fold random forest | - Limited Focus on Real-Time Validation - Lack of Dynamic Resource Allocation |

### A. IoT and Sensor Layer

The IoT and Sensor Layer plays a pivotal role in the continuous collection of real-time data from the patient, utilizing a variety of physiological and camera sensors. Physiological sensors continuously monitor key health parameters, including heart rate (HR), blood pressure (BP), and cholesterol levels. The data collected from these sensors serves as the primary input for evaluating the patient's health condition and is subsequently fed into the predictive AI model for heart attack prediction and other critical health assessments. In emergency situations, the camera captures video feeds that offer visual context regarding the patient's physical state. This visual data complements the physiological measurements and enhances the overall understanding of the patient's condition, particularly during critical events.

### B. Edge Computing Layer

The Edge Computing Layer is the central layer in this work, responsible for processing the patient's health data from physiological sensors using an AI model for heart attack prediction. The camera is activated only in critical situations to capture video frames, ensuring privacy. A Deep Q-Network (DQN) model is used to decide whether to process the data locally on the Raspberry Pi or offload it to the Fog Layer, optimizing resource usage. Once processed, all data, including health metrics and video frames, are transmitted from the Fog

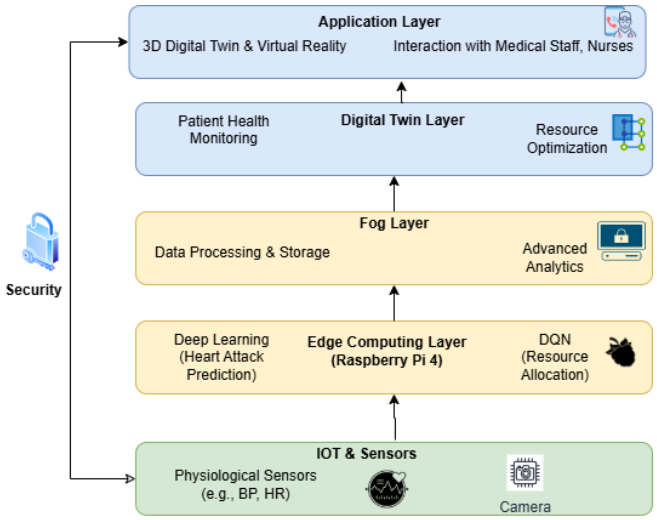


Fig. 1. Multi-layer architecture of the proposed framework for heart attack prediction and resource allocation, integrating IoT sensors, edge computing, fog, and digital twin technology.

or Raspberry Pi to the Digital Twin Layer. This data allows for the continuous update of the virtual model, supporting real-time health monitoring and decision-making.

*1) AI Driven heart attack risk prediction at the edge:* We trained an IA model for heart attack prediction using a hybrid convolutional neural network (CNN) and bidirectional long-short-term memory (BiLSTM) architecture. This model was specifically designed to predict heart attacks based on physiological data, including heart rate, blood pressure, and cholesterol levels. The model was trained and deployed on a Raspberry Pi 4B, which features a quad-core Cortex-A72 processor and 4GB of RAM, providing sufficient computational power for edge-based inference.

*a) Dataset:* In this study, the data set from the UCI machine learning repository dataset is used . Data in the dataset are collected from the Hungarian Institute of Cardiology, Cleveland clinic foundations. It consists of information on patient records both normal and abnormal. This database contains 76 attributes, with a total of 303 observations. The attributes are age, sex, resting blood pressure, cholesterol, etc. And the data set consists of six missing values. In 303 observations, 138 are normal persons, and 165 are abnormal persons, i.e., sufered from heart disease.

*b) CNN-BiLSTM Architecture:* Our proposed hybrid CNN-BiLSTM model leverages Convolutional Neural Networks (CNNs) for feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) layers for sequential learning, effectively capturing both spatial and temporal dependencies to enhance prediction accuracy. The architecture, illustrated in Fig. 2, consists of a CNN layer followed by a dropout of 0.5, a BiLSTM layer with 64 units, and a fully connected layer. The model was trained for 200 epochs with a learning rate of 0.0025, utilizing the softmax activation function.

*c) CNN:* CNN has been effectively used in image processing, face recognition and time series analysis, among other applications[33].It is possible to construct CNN architecture by stacking three primary layers: convolution, pooling, and fully

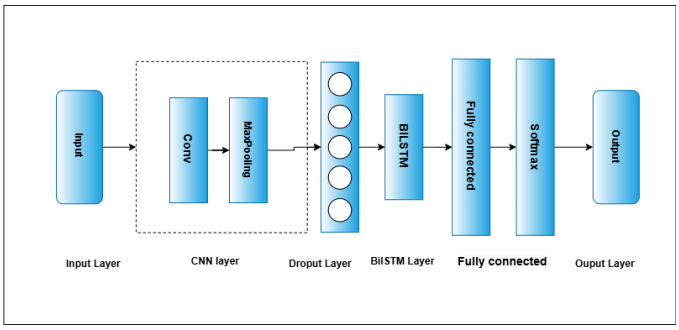


Fig. 2. CNN-BILSTM architecture.

connected (FC). Every convolution layer has a set of learnable filters whose objective is to automatically extract local characteristics from the input matrix using the learned filters. It is possible to minimize the complexity of the computational load and improve model performance by using filters that execute convolution operations based on two essential notions, namely weight sharing and local connection, which may be achieved via filters [34].

*d) BiLSTM:* As an extension to RNNs, Long Short-Term Memory (LSTM) is introduced to remember long input data and thus the relationship between the long input data and output is described in accordance with an additional dimension (e.g., time or spatial location). An LSTM network remembers long sequence of data through the utilization of several gates such as: 1) input gate, 2) forget gate, and 3) output gate. The deep-bidirectional LSTMs (BiLSTM) networks are a variation of normal LSTMs, in which the desired model is trained not only from inputs to outputs, but also from outputs to inputs. More precisely, given the input sequence of data, a BiLSTM model first feed input data to an LSTM model (feedback layer), and then repeat the training via another LSTM model but on the reverse order of the sequence of the input data (i.e., Watson-Crick complement [35].

In this work we proposed A hybrid model for predicting heart disease using CNN and BiLSTM algorithms.

*e) Evaluation metrics:* The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score, ensuring its effectiveness in real-time heart attack prediction.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

$$\mathrm{T}_{\text{inference}}(\text{ms}) = \mathrm{T}_{\text{out}} - \mathrm{T}_{\text{inp}} \tag{5}$$

Where:

- $TP$ (True Positive): The number of correctly identified heart attack cases, where the model accurately predicts a heart attack event.
- $FN$ (False Negative): The number of heart attack cases that were not predicted by the model, indicating missed detections of actual heart attacks.
- $FP$ (False Positive): The number of instances where the model incorrectly predicts a heart attack, leading to false alarms for non-heart attack events.
- $TN$ (True Negative): The number of correctly identified non-heart attack cases, where the model accurately predicts the absence of a heart attack.
- $\mathrm{T}_{\text{inp}}$: The timestamp when the physiological data (e.g., heart rate, blood pressure) is fed into the prediction model for analysis.
- $\mathrm{T}_{\text{out}}$: The timestamp when the heart attack prediction result is generated, marking the point at which the model's decision is outputted for clinical assessment.

*2) Allocation resources model using DQN (Deep Q-Network):* Resource allocation in an Edge-Fog environment presents a significant challenge due to the diverse nature of tasks, fluctuating workloads, and the stringent demands for low latency. Achieving an optimal balance between local processing (Edge) and offloading to the Fog requires quick, adaptive decision-making to ensure minimal latency, maximize resource efficiency, and control costs effectively. The Deep Q-Network (DQN) emerges as a promising solution, enabling autonomous learning to make optimal decisions in complex and dynamic environments [36]. In the context of healthcare, particularly in heart attack prediction, intelligent Edge-Fog resource management can enhance prediction accuracy and, more importantly, save lives by ensuring the rapid and reliable processing of critical data.

- DQN Concepts: The Deep Q-Network (DQN) is a reinforcement learning algorithm that combines Q-learning, a table-based control method, with deep neural networks. Q-learning problems are typically framed as Markov Decision Processes (MDPs), which consist of pairs of states ($s_t$) and actions ($a_t$). State transitions occur with a transition probability ($p$), a reward ($r$), and a discount factor ($\gamma$). The transition probability $p$ reflects the likelihood of transitioning between states and receiving associated rewards. According to the Markov property, the next state and reward depend only on the previous state ($s_{t-1}$) and action ($a_{t-1}$)[37]. Traditional Q-learning struggles to handle large-scale or continuous-space MDPs due to the *curse of dimensionality* in the Q-table. To address this issue, DeepMind introduced the DQN algorithm, which approximates the Q-table using deep neural networks. In DQN, the $Q$ value of each action can be predicted by simply inputting the current state ($s_\tau$) into the network, simplifying computation. The DQN uses a deep neural network $Q(s, a; \omega)$, parameterized by weights $\omega$, to approximate the value function $Q(s, a)$. In this framework, the agent is responsible for learning, while the environment provides the interaction context [38]. The primary objective of the agent is to learn optimal actions that maximize cumulative rewards. The agent selects actions ($a_\tau$) and trains the neural network, while the environment updates the state ($s_t$) and computes the reward ($r_t$). The DQN employs two neural networks , the evaluation network (*eval-net*) and the target network (*target-net*), which share the same architecture [39]. The *eval-net* estimates $Q$ values, while the *target-net* provides stable $Q$ values as targets for training. The $Q$ values are updated using a modified Bellman equation:

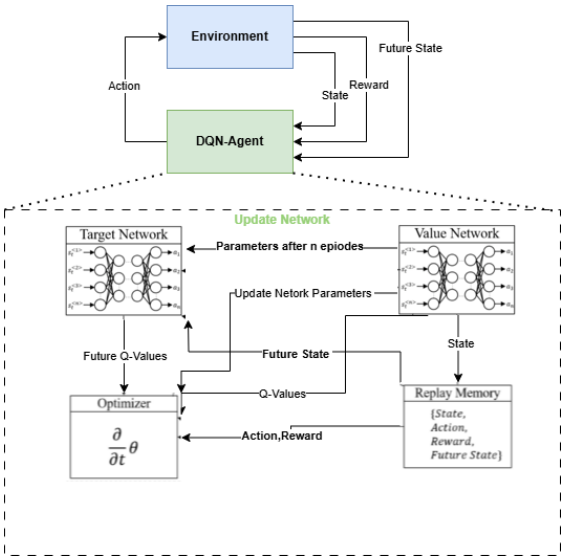


Fig. 3. Concept of DQN.

$$Q'(s_t, a_t) = Q(s_t, a_t) + \alpha \left[ r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right] \tag{6}$$

where $Q(s_t, a_t)$ and $Q'(s_t, a_t)$ are the current and updated $Q$ values for a given action $a$ in state $s$ at time $t$, $\alpha$ is the learning rate (typically a small positive value), $r_{t+1}$ is the reward received after performing the action, $\gamma$ is the discount factor (close to but less than 1), and $\max_a Q(s_{t+1}, a)$ represents the highest estimated $Q$ value for the next state $s_{t+1}$. This approach allows DQN to learn effectively in complex environments by leveraging the power of deep neural networks. The specific process is shown in figure [3]

- System model and problem formulation: This hybrid model aims to optimize resource allocation in an Edge-Fog Computing environment for an efficient healthcare system. It combines reinforcement learning with the physical constraints of the Raspberry Pi's resources.
- System Variables: ($R_a$, $C_a$, $B_a$) are the resources in RAM, CPU, and Bandwidth, respectively, available on the Raspberry Pi board, ($L_t$) is the maximum

acceptable latency for processing data, $(T_m)$ is the maximum operating temperature of the Raspberry Pi, and $(P)$ is the prediction result (0 = normal, 1 = critical).

- Consumption Variable: $(R_u,\ C_u,\ B_u\ )$ are the resources in RAM, CPU, and Bandwidth, respectively, necessary for local processing, $L_c$ is the current time measure, and $T_c$ is the current temperature of the Raspberry Pi.

The resource constraints to ensure the optimal functioning of the system are given by:

$$\text{RAM: } R_u \le R_a, \quad \text{CPU: } C_u \le C_a, \quad \text{Bandwidth: } B_u \le B_a, \quad \text{Latency: } L_c \le L_t, \quad \text{Temperature: } T_c \le T_m. \tag{7}$$

The reward function $R$ assesses the effectiveness of resource allocation:

$$R = \alpha_1 \cdot \text{RAM\_efficiency} + \alpha_2 \cdot \text{CPU\_efficiency} + \alpha_3 \cdot \text{Bandwidth\_efficiency} - \beta \cdot \text{Latency\_penalty}$$

où :

$$\text{RAM\_efficiency} = \frac{R_a - R_u}{R_a}$$

$$\text{CPU\_efficiency} = \frac{C_a - C_u}{C_a}$$

$$\text{Bandwidth\_efficiency} = \frac{B_a - B_u}{B_a} \quad \text{(si offload vers Fog)}$$

$$\text{Latency\_penalty} = \max(0, L_c - L_t)$$

The coefficients $\alpha_1$, $\alpha_2$, $\alpha_3$, and $\beta$ are adjusted according to the relative importance of the resources. The allocation decision $a$ is made as follows:

- If all constraints are satisfied locally:

$$R_u \le R_a, \quad C_u \le C_a, \quad T_c \le T_m, \quad B_u \le B_a, \quad L_c \le L_t. \tag{8}$$

  then $a = 0$ (Local processing).

- Otherwise, if one or more constraints are not satisfied, or if the reward is lower locally, then $a = 1$ (Transfer to Fog).

Require: Discount factor $\gamma$, exploration rate $\epsilon$, replay memory capacity $P$, heart attack prediction model $HA\_model$, DQN model $DQN\_model$.

### C. Fog Layer

In our system, after the Deep Q-Network (DQN) model runs on the Raspberry Pi to determine whether data should be processed locally or offloaded, the Fog Layer becomes essential. When the Raspberry Pi is unable to process more complex data, such as video frames captured by the camera, it transmits this data to the Fog Layer. The Fog Layer then processes these larger, more computationally demanding

**Algorithm 1** DQN-Based Resource Allocation for Heart Attack Prediction (DQNRAP)

Initialize replay memory $D$ to capacity $P$.
Initialize evaluation network with parameters $\theta$.
Initialize target network with parameters $\theta' = \theta$.
Connect to Azure IoT Hub for Digital Twin synchronization.
Configure interval $T_{pred} = 0.1$ sec, buffer size $N_{threshold} = 2$.
Initialize camera to standby mode.
**for** each episode $k$ **do**
    Initialize initial state $s_1$ by collecting sensor data (IMU, temperature, heart rate).
    **for** each step $t$ **do**
        Collect real-time sensor data $Inputdata$.
        Predict heart attack status:

$$prediction = HA\_model.predict(Inputdata)$$

        Threshold Prediction:

$$heart\_status = \begin{cases} 1 & \text{if } prediction > 0.5 \quad \text{(Critical)} \\ 0 & \text{otherwise (Normal)} \end{cases}$$

        Update Buffer with $heart\_status$.
        **if** $\sum(buffer[-N_{threshold}:]) = N_{threshold}$ **then**
            Activate camera for 1-minute video capture.
            Set $camera\_status = 1$.
        **end if**
        Construct State:

$$s_t = [RAM, CPU, Latency, Bandwidth, Temperature]$$

        Generate random number $h \in [0, 1]$.
        **if** $h < \epsilon$ **then**
            Randomly select action $a_t$.
        **else**
            $a_t = \arg\max_a Q(s_t, a; \theta)$.
        **end if**
        Execute action $a_t$ (local processing or fog offloading).
        Observe reward $r_t$ and next state $s_{t+1}$.
        Store Transition $(s_t, a_t, r_t, s_{t+1})$ in $D$.
        Update Evaluation Network (Algorithm 2).
        **if** $t\%C == 0$ **then**
            Reset Target Network: $\theta' = \theta$.
        **end if**
        Synchronize data with Azure IoT Hub:

$$payload = \{timestamp,\ heart\_status,\ camera\_status,\ RAM,\ CPU,\ Latency,\ Bandwidth,\ a_t\}$$

    **end for**
**end for**

**Algorithm 2** Evaluation Network Update

1: Sample mini-batch $(s, a, r, s')$ from $D$.
2: Compute target $Q'$ value:

$$Q' = r + \gamma \max_{a'} Q(s', a'; \theta')$$

3: Update $Q$-network by minimizing loss:

$$Loss = (Q(s, a; \theta) - Q')^2$$

**Algorithm 3** Routing Decision

1: **if** $a_t = 1$ **then**
2: Process video locally (Raspberry Pi).
3: **else**
4: Offload data to Fog.
5: **end if**

datasets, enabling efficient data handling and ensuring that the local resources are not overwhelmed. This approach optimizes the overall system performance by leveraging the Fog Layer's ability to handle more intensive computations.

### *D. Digital Twin Layer*

The Digital Twin Layer generates a real-time virtual model of the patient, continuously updated with data from IoT sensors to monitor health status and optimize resource allocation. Leading cloud platforms, such as Amazon Web Services (AWS) and Microsoft Azure, offer solutions for building digital twins. In our work, we utilize Azure * to develop a digital twin that simulates the patient's heart condition, visualizing processed data from the camera and storing historical records. This enhances overall system prediction accuracy and improves resource allocation through predictive analytics. The Fig. 4 represents a JSON program fragment of the prediction of the IA heart attack model and also the resource allocation if data of camera will be processed at edge or transferred to the fog.the digital twin will be used to monitor the heart status and control the process of data between the edge and the fog computing .

### *E. Application Layer*

The Application Layer leverages 3D digital twin models and virtual reality to enhance patient monitoring and emergency response. The digital twin continuously updates with real-time data, providing a visual representation of the patient's heart condition. When critical situations are detected, the system automatically notifies medical staff and family members for immediate intervention. Beyond monitoring, the digital twin plays a vital role in refining the heart attack prediction and resource allocation models by analyzing historical data and improving decision accuracy. This ensures better healthcare management and faster response in emergencies.

## IV. Results and Discussion

### *A. Result of Heart Attack Prediction Model*

This section presents the experimental results obtained from testing the heart attack prediction model on both a PC and edge devices. Initially, the CNN-BiLSTM model was evaluated on the PC to assess its performance. Following this, the model was transferred to the Raspberry Pi 4B, where its accuracy, size, and inference time were validated.

*https://azure.microsoft.com/fr/products/digital-twins/

```
{
  "id": "dtmi:example:CardiacHealthTwin;1",
  "@type": "Interface",
  "displayName": "Cardiac Health Twin",
  "contents": [
    {
      "@type": "Property",
      "name": "HeartDisease",
      "schema": "integer",
      "description": "Indicates whether the patient
        has heart disease (1 for yes, 0 for no)."
    },
    {
      "@type": "Property",
      "name": "ResourceAllocation",
      "schema": "integer",
      "description": "Allocation of processing
        resources: 0 for Edge, 1 for Fog."
    }
  ]
}
```

Fig. 4. JSON Program fragment of the patient status for Azure DT.

TABLE II. Classification Report for the Heart Attack Prediction Model

| Class | Precision | Recall | F1-score |
|---|---|---|---|
| 0 | 0.9722 | 1.0000 | 0.9859 |
| 1 | 1.0000 | 0.9608 | 0.9800 |
| **Accuracy** | | 0.9835 | |
| **Macro avg** | 0.9861 | 0.9804 | 0.9830 |
| **Weighted avg** | 0.9839 | 0.9835 | 0.9834 |

The results presented in Table II, Fig. 5, and 6 highlight the performance of our model, which achieved an overall accuracy of 98.35%. As shown in the confusion matrix in Fig. 5), the model correctly classified all instances of Class 0, resulting in a perfect classification rate of 100%. However, Class 1 achieved a slightly lower accuracy of 96.08%, with 3.92% of instances misclassified as Class 0.The classification report in Table II further demonstrates the effectiveness of our trained model. For Class 0 (No Attack), the precision is 97.22%, recall is 100%, and the F1-score is 98.00%. For Class 1 (Heart Attack), the model achieves a precision of 1.000, recall of 96.08%, and an F1-score of 98.00%.The macro and weighted averages further confirm that the model handles both classes effectively, exhibiting minimal bias while maintaining high precision, recall, and F1-scores. Additionally, the ROC curve Fig. 6 showcases the model's near-perfect ability to distinguish between the two classes, with an impressive Area Under the Curve (AUC) of 0.99.

*1) Comparison of proposed heart attack prediction models with related works:* To validate the effectiveness of our proposed hydrid CNN-BiLSTM heart attack prediction model, we compared it with existing models in the literature. This

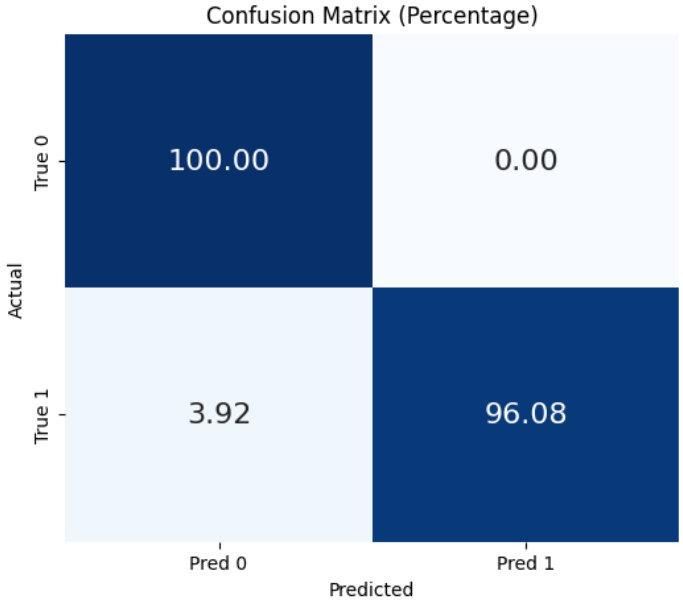


Fig. 5. Confusion matrix for the heart attack prediction model.

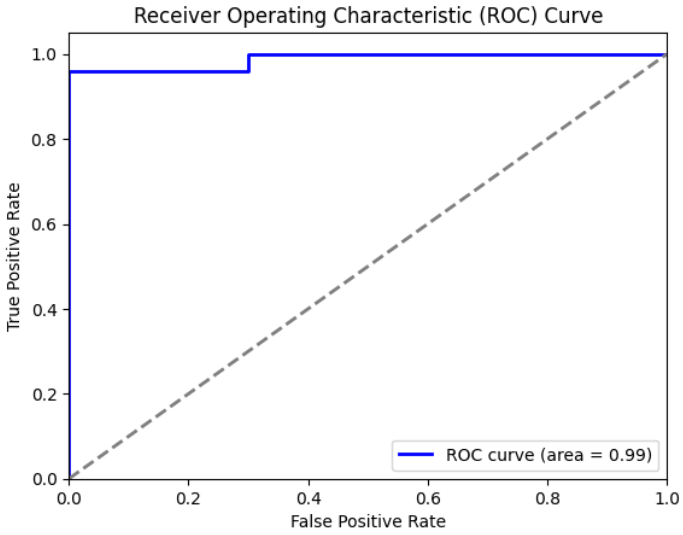


Fig. 6. Confusion matrix for the heart attack prediction model.

comparison highlights differences in model architectures using the same data set. Table III summarizes the results of the comparison using the accuracy metric of key related works.

*2) Comparison of heart attack prediction models using the same Cleveland dataset:* The results in III indicate that our proposed CNN-BiLSTM model achieves superior accuracy compared to traditional architectures, benefiting from the combination of convolutional and bidirectional long short-term memory (BiLSTM) layers. This hybrid architecture enhances feature extraction and temporal modeling, leading to more precise predictions.

TABLE III. COMPARISON OF HEART ATTACK PREDICTION MODELS

| Date | Authors | Model Architecture | Accuracy (%) |
|---|---|---|---|
| 2022[40] | Abdelghani et al. | LR algorithme | 82,6 |
| 2023[27] | Sudha V K et al. | CNN-LSTM | 89 |
| 2024[25] | Dritsas et al. | CNN-GRU | 91 |
| 2024[41] | Remya et al. | CNN- UMAP algorithm | 91 |
| 2024[42] | Bouqentar et al. | SVM | 92 |
| 2023[34] | Shrivastava et al. | CNN-BiLSTM | 96.66 |
| **2024** | **Ours proposed Methode** | **CNN-BiLSTM** | **98.34** |

## B. Result of Allocation Resource Model Using DQN

The result of Fig. 7 shows the evolution of average cumulative rewards over episodes in the DQN model. Initially, the agent receives low rewards, but gradually improves its decisions. After approximately 200 episodes, the rewards stabilize around 50, indicating that the agent has learned an optimal strategy and that its learning process has effectively converged. Fig. 8 represents the decay of epsilon $\epsilon$, a key parameter in DQN that regulates the balance between exploration and exploitation.

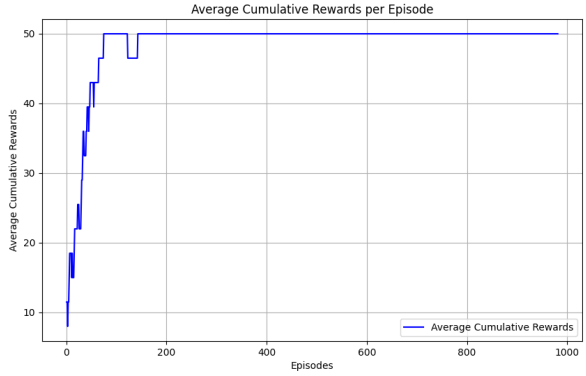


Fig. 7. Average cumulative rewards.

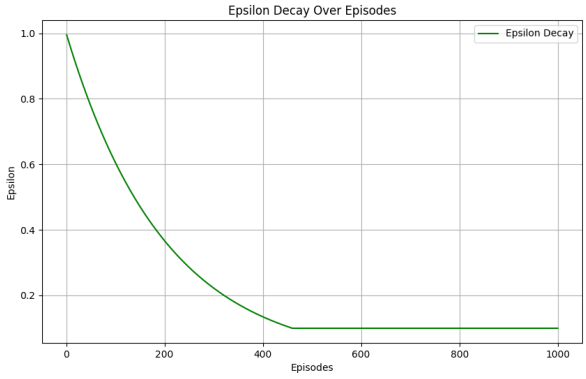


Fig. 8. Epsilon decay.

At the beginning, $\epsilon$ is high ($\sim 1$), allowing the agent to explore various actions. As training progresses, $\epsilon$ decreases, encouraging the agent to rely more on decisions that have produced the best rewards. After ($\sim 400$) episodes, $\epsilon$ becomes very low, which means that the agent has learned enough

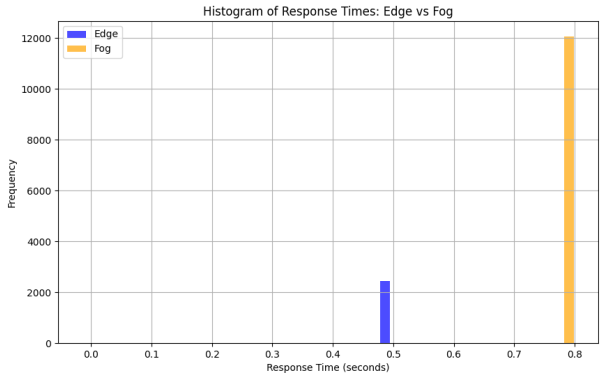


Fig. 9. Response times.

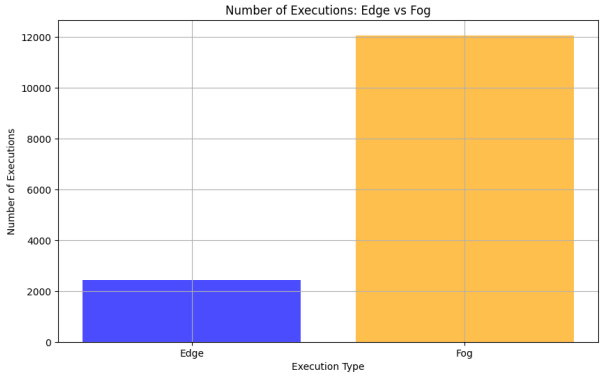


Fig. 10. Execution count.

and now relies primarily on optimal choices. These two main results complement each other: the decrease in $\epsilon$ explains the stabilization of cumulative rewards, confirming that the DQN model learns progressively, efficiently and optimally.

The study 9 displays a response time histogram comparing Edge and Fog processing. The Edge responses are significantly faster (0.5s), whereas Fog responses take longer (0.8s), indicating a higher processing delay in the Fog environment. The 10 shows that the majority of executions (over 12,000) take place in the Fog, compared to only 2,500 in the Edge.

### C. Discussion

The results indicate excellent performance of the prediction model based on a hybrid CNN-BiLSTM network, with high precision and reliability metrics (see Fig. 5 and Fig. 6). This level of performance is crucial in critical scenarios such as cardiac event prediction, where false negatives could have severe consequences.In terms of resource allocation, the Deep Q-Network model demonstrates fast and efficient learning capabilities (Fig. 7 and Fig. 8), dynamically adapting to maximize system performance. Most processing decisions were offloaded to the Fog (Fig. 10), which suggests that critical tasks require more computing power than what is available at the Edge. Regarding latency, the results in Fig. 9 show that the proposed approach ensures fast processing—an essential factor in real-time medical monitoring scenarios. By integrating artificial intelligence and deep learning techniques into a Fog/Edge architecture, the system succeeds in ensuring both diagnostic accuracy and responsiveness while optimizing resource utilization.

## V. Conclusion and Future Work

In this study, we proposed an intelligent and adaptive system for real-time cardiac event prediction and resource allocation in Edge-Fog Computing environments. By integrating a deep learning-based CNN-BiLSTM model for heart attack prediction and a Deep Q-Network (DQN) for dynamic resource management, our approach demonstrates the potential to enhance real-time monitoring and response efficiency in healthcare applications. Furthermore, the incorporation of digital twins into our architecture enables continuous system optimization and predictive analysis, reinforcing the reliability and adaptability of the proposed framework. Experimental results indicate that our model effectively manages workload distribution, reduces latency, and improves decision-making for critical healthcare scenarios. The ability to dynamically allocate resources between edge and fog computing environments ensures optimal system performance, even under fluctuating workloads. Our approach is highly relevant to the context of Mauritania, where cardiovascular diseases represent a significant public health challenge. It also aligns with the national goal of reducing the mortality rate from these diseases by 33% by 2030.

Future work will focus on enhancing the system's capabilities by developing an AI model at the fog level to process video data transferred from edge devices, optimizing real-time analysis and reducing latency. Additionally, we aim to improve the digital twin component to refine AI model efficiency and enhance system adaptability, leading to better overall performance. To further strengthen privacy and scalability, we will incorporate federated learning techniques, enabling decentralized model training without compromising sensitive patient data. Ultimately, our research paves the way for a more responsive and intelligent healthcare infrastructure, capable of providing real-time cardiac monitoring with high accuracy while optimizing computational resources effectively.

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# Predicting Multiclass Java Code Readability: A Comparative Study of Machine Learning Algorithms

Budi Susanto, Ridi Ferdiana, Teguh Bharata Adji
Department of Electrical and Information Engineering-Faculty of Enginering,
Universitas Gadjah Mada, Indonesia

***Abstract*—The classification of program code readability has traditionally focused on two target classes: readable and unreadable. Recently, it has evolved into a multiclass classification task in three categories: readable, neutral, and unreadable. Most of the existing approaches rely on deep learning. This study investigated the multiclass classification of Java code readability using four feature metric datasets and 14 supervised machine learning algorithms. The dataset comprises 200 labeled Java function declarations. Readability features were extracted using Scalabrino's tool, generating three datasets: Scalabrino, Buse-Weimer, a combined set (Dall), and a fourth (Dcorr) via feature selection based on interfeature correlation. Each model underwent hyperparameter tuning via a Randomized Search and was evaluated through 30 iterations of a five-fold cross-validation. Scaling techniques (MinMax, Standard, Robust, and None) were also compared. The best performance, with an average accuracy of 61.1% and minimal overfitting, was achieved by Random Forest with MinMax scaling on Dcorr. Feature importance analysis using permutation methods identified 22 key metrics related to comments: code complexity, syntax, naming, token usage, and density. Despite its moderate accuracy, the findings offer valuable insights and highlight essential features for advancing code readability research.**

***Keywords*—Code readability; machine learning; multiclass classification; hyperparameter tuning; future selection**

## I. Introduction

Reading source code is common for software developers, and readability significantly affects the software quality [1]. While readability pertains to the ease of reading code syntax, comprehensibility involves understanding code semantics [2]. These two concepts are related, but distinct, and readability may fluctuate throughout the software lifecycle, thereby affecting comprehensibility [3].

Automated classification methods have been widely used to predict code readability, typically categorizing it as "readable" or "unreadable." Various machine learning techniques, such as Logistic Regression, Bayesian Networks, Perceptron, Random Forest, and Support Vector Machines (SVM), have been applied to classify code readability into two labels, as demonstrated by researchers such as Buse and Weimer [4] and Scalabrino et al. [5].

Posnett et al. [6] developed a regression model for classifying source code readability into two classes. Dorn [7] also utilized logistic regression to determine the weights of various features to construct a readability metric model for source code. Mi et al. [8]–[10] further explored convolutional neural network (CNN)-based architectures and hybrid neural network models for two-class readability classifications.

Recent advancements have extended the readability classification into three categories: "readable," "neutral," and "unreadable" [11]. Mi et al. [11], [12] employed convolutional neural networks (CNNs) and graph neural networks (GCNs) for this task. The GCN model achieved state-of-the-art accuracy, reaching 72.5% for a three-class classification [11]. These models were trained on a Java corpus from Scalabrino et al. [13] containing 200 Java function declaration snippets. Overall, the research findings indicate that deep learning-based methods outperform traditional machine learning approaches in terms of readability classification accuracy.

However, existing comparative studies have predominantly focused on binary readability classification tasks. In contrast, limited attention has been given to the more complex three-class readability classification, which involves categorizing code as "readable," "neutral," or "unreadable." The state-of-the-art model addressing this task proposed by Mi et al. [11] employs a Graph Neural Network (GNN) framework. The research gap lies in the insufficient exploration of alternative machine learning classification approaches for this three-class problem, which may offer competitive or complementary performance to GNN-based methods. In light of this, further empirical investigation is warranted to evaluate the effectiveness of diverse machine learning algorithms in handling multiclass code readability classification.

This study comprehensively evaluated 14 classification methods applied to several code readability metrics: Buse and Weimer (BW), Scalabrino (Scal), and a combination of BW, Scal, and Posnett metrics. To enhance the classification performance, we employed two feature selection methods: one based on feature correlation and its relationship with target classes, and another based on the importance scores derived from the best-performing classification method. The dataset used in this experiment consisted of Java code snippets from Scalabrino et al. [13], which were categorized into three readability classes by Mi et al. [11] with a 1:2:1 ratio for readable, neutral, and unreadable classes. Each classification method was optimized for hyperparameter tuning using a Randomized Search method. Huyen [14] stated that the random search method is a form of soft AutoML.

This study aimed to address two key research questions: RQ1: Which classification method performs best? We investigated 12 classification methods and two calibration techniques for the Gaussian Naïve Bayes classifier to classify the Java corpus from Scalabrino et al. into three readability classes established by Mi et al. The evaluation metrics used included the accuracy and weighted F1 scores. Our analysis aims to provide a comparative overview of the performance of three-class

readability classifiers in state-of-the-art models [11]. RQ2: Which features contribute the most to the best-performing classification method? The most important features were based on the best-performing model in the three-class readability classification for each classification method. Identifying these key features will be the foundation for developing improved source code readability metrics.

The remainder of this paper is organized as follows. The background and related works in Section II reviews the related literature, focusing on previous research in program code readability classification, particularly multiclass classification approaches using machine learning techniques. The methodology in Section III outlines the methodology, details the dataset used, classification models applied, and evaluation framework. The results and discussion in Section IV presents the experimental results and discussion of the findings, including a comparative analysis of the classification performance. The conclusion in Section V concludes the study by summarizing key insights, highlighting contributions, and suggesting directions for future research.

## II. Background and Related Works

### A. Code Readability Metrics

Evaluating code readability is a complex challenge because of its inherently subjective nature. Various metrics that consider factors such as code size, entropy, and structural properties have been proposed [6]. However, these metrics often fail to align with developers' perceptions of readability improvements [15]. Fakhoury et al. [15] utilized Scalabrino's, Dorn's, and combined Buse-Weimer and Posnett metrics to classify code readability based on changes made by programmers. Their findings suggested incorporating additional features, such as the number of incoming invocations and code styling elements, into code readability metrics.

Furthermore, textual features such as identifiers and comments have been shown to provide valuable supplementary information beyond structural characteristics [13]. Other factors, including coding style, application domain [16], structural constraints, and programming paradigms (e.g., reactive programming) [17] also influence readability assessments. Moreover, further evidence is required to clarify the impact of specific attributes, such as code size, complete-word identifiers, and comments, on readability and understandability [18]. These challenges underscore the need for more versatile and adaptive readability metrics from the perspectives of various programming styles and developers.

Predicting the readability of source code involves extracting several features from code snippets, collectively referred to as code readability metrics. Extensive research has been conducted to develop readability metrics. Buse and Weimer [4] focused on structural characteristics, whereas Dorn [7] introduced visual and spatial (metric based) characteristics. Scalabrino et al. [5] extended these metrics by incorporating textual characteristics. Alawad et al. [19] enhanced Buse and Weimer metrics using text readability metrics such as the Automated Readability Index (ARI). Mi et al. [9] defined readability features in terms of visual, structural, and semantic characteristics that are represented as embedding vectors. Additionally, Mi et al. [11] introduced a representation combining Abstract Syntax Tree (AST) graphs with data and control flow extracted from the source code.

Buse and Weimer defined 25 attributes to develop a readability classification model, categorizing readability into two classes: more and less readable. Posnett et al. [6] simplified Buse and Weimer's parameters into three attributes to construct a readability weight-based model. Dorn [7] identified approximately 59 code attributes, focusing on visual, spatial, and linguistic aspects. Scalabrino et al. [5] defined 20 attributes related to the textual properties and structural characteristics. Choi et al. [20] proposed seven attributes for linear regression modeling to derive readability weights for the source code. Mi et al. [21] extracted character-level, token-level, and node-level representations of the source code and applied them within a Convolutional Neural Network (CNN). Mi et al. [9] further advanced this approach by extracting visual codes, tokens, segment embeddings, and character metric representations for structural modeling. Readability classification models have been applied to two primary categories: readable and unreadable.

### B. Methods for Measuring Code Readability

Several manual and heuristic methods have been developed to assess the readability of program codes. Although these methods are not explicitly designed for readability measurement, they provide approaches for evaluating code complexity, maintainability, and human-scale readability indicators. Some of these methods include syntactic-based metrics, such as variable length, lines of code (LOC), and cyclomatic complexity, which serve as potential indicators for measuring code readability, and structure and logic-based metrics, which evaluate code readability by analyzing the structural aspects of the code, including loops, branching, and function separation.

Well-structured modular code is generally easier to read and understand. Several types of metrics are commonly used to evaluate readability. Rule-based metrics focus on adherence to coding conventions, such as the use of descriptive variable names, consistent formatting, and sufficient comments [22]. Tools such as Checkstyle[1] and Pylint[2] automatically check and enforce these rules. Complexity metrics assess the readability by measuring the logical complexity of a code. For example, Halstead metrics estimate how difficult it is for a program to understand and maintain, whereas cognitive complexity metrics [23] account for factors such as deep nesting and long conditional statements that may make it harder to follow. Among the complexity metrics and code readability metrics, Tashtoush and Darwish [24] asserted that there is an influence between these two metrics. This empirical study explored the bidirectional relationship between code readability and software complexity by using 12,180 Java files from the Eclipse project. By applying machine learning models, particularly decision trees, to 25 readability features (based on Buse and Weimer) and seven complexity metrics, the study achieved over 90% accuracy in predicting how readability influences complexity and vice versa. Key contributing factors include formatting-related features (e.g., indentation and character usage) and complexity measures such as Halstead volume.

[1] https://checkstyle.sourceforge.io/
[2] https://www.pylint.org/

This study also challenges prior assumptions by showing that readability features are influenced by code size, thereby offering new insights into improving software quality and maintainability.

Finally, human-scale indicators rely on developers direct assessments of code readability. These evaluations are often used as training data for machine learning models that aim to automatically predict code readability [4], [13]. These approaches seek to align readability metrics with how developers perceive the code quality. To capture what programmers do to make source code more readable, Roy et al. [25] analyzed the history of programmer code changes. This study introduces a machine learning model that detects incremental readability improvements in source code aligned with developer perceptions. Trained on 2,781 manually validated Java file changes, the model leveraged static code metrics before and after commits and achieved 79.2% precision and 67% recall. Key insights reveal that readability improvements typically involve modifications to existing lines, whereas non-readability changes add new lines. This study lays the groundwork for integrating readability scoring into code review tools to support more efficient evaluation of code changes. Future research could explore how large language models influence code readability [26] as well as the development of more advanced readability models that adapt to the continual evolution of software development practices.

## III. Methodology

Fourteen machine learning algorithms for multiclass classification of code readability were evaluated using a dataset of 200 Java code snippets from Scalabrino et al. [13], which were categorized into three readability classes by Mi, et al. [11]. Mi et al. used a systematic approach to establish three categories of code readability in their study. This study used a dataset originally compiled by Scalabrino et al. [13] consisting of 200 code fragments extracted from four open-source Java projects: jUnit, jHibernate, jFreeChart, and ArgoUML. These fragments ranged from 10 to 50 lines of code and were free of syntax errors, ensuring that the readability evaluation was unaffected by syntax or compilation issues.

The dataset was then divided into three readability groups based on Scalabrino's readability score: easy to read (top 25%), difficult to read (bottom 25%), and neutral (middle 50%). This classification follows a 1:2:1 ratio, allowing for meaningful comparison with Scalabrino's two-class readability distribution. Additionally, this distribution more accurately reflects real-world scenarios, in which neutral readability is more common than extreme readability or legibility.

From these 200 Java code snippets, a set of readability metric values were derived based on the readability metrics proposed by Scalabrino, Buse-Weimer, and Posnett. These metric values were computed using the Readability Assessment Tool[3] provided by Scalabrino et al. [5]. Scalabrino's tool generates 110 attributes representing values from the Scalabrino, Buse-Weimer, Posnett, and Dorn models. Upon analysis, it was found that 12 of Dorn's 59 attributes had over 41.5% missing values across 200 data points. Consequently, Dorn's attributes and readability score attributes from the Scalabrino, Buse-Weimer, and Posnett models were excluded, leaving 48 attributes for the classification experiment. The combined dataset with the 48 selected attributes was labeled as $D_{all}$.

[3]https://dibt.unimol.it/report/readability/files/readability.zip

TABLE I. Metrics with > 10% Outliers among 200 Samples

| No. | Attribute | % outlier data |
|---|---|---|
| 1 | Scalabrino.expression_complexity_maximum | 41.0% |
| 2 | Scalabrino.number_of_senses_maximum | 27.5% |
| 3 | BW.loops_average | 23.0% |
| 4 | BW.comments_average | 14.5% |
| 5 | Scalabrino.abstractness_words_maximum | 14.5% |
| 6 | BW.operators_average | 13.0% |
| 7 | Scalabrino.commented_words_average | 11.0% |

Based on the definition of $D_{all}$ metric features, this study created another dataset containing the definition of a series of feature metrics based on the scalabrino model ($D_{scal}$ uses 20 feature metrics) and Buse-Weimer model ($D_{bw}$ uses 25 feature metrics). Both feature metric definitions are subsets of the entire metric feature set. The purpose of this is to measure how well the Scalabrino and Buse–Weimer models perform in multiclass code readability classification.

Regarding the characteristics of the $D_{all}$ dataset with 200 data points and 48 attributes when analyzed using the Interquartile Range (IQR), seven metric attributes (14.58%) can be said to have outlier data of more than 10%. Table I displays the seven metric attributes whose data had more than 10% detection as outliers. One approach that can be applied to handle outlier data is data scaling [27]. Therefore, this study applies a configuration with three scaling techniques: Standard, Minmax, and Robust.

Fig. 1 illustrates the workflow of the classification experiment. The process begins with the formation of a dataset using Scalabrino et al.'s Readability Assessment Tool, applied to a corpus of Java code snippets categorized into three readability classes by Mi et al. [11]. This recalculation is necessary to ensure that the attribute values are derived directly from the code snippet dataset, which consists of function declarations written in Java. The tool generates attribute values based on the readability metrics proposed by Scalabrino, Buse, Weimer, and Posnett. The generated values were then converted into a CSV file. The final dataset consists of attribute values and three corresponding readability class labels.

Based on $D_{all}$, this study calculates the correlation between each attribute, including the target classification label. This feature correlation analysis step was performed to identify highly correlated metric features. Attribute analysis of the combined dataset $D_{all}$ was performed by examining the correlation value between its attributes. Correlation-based attribute selection uses the minimum correlation value as the constraint ($\geq$ 0.4 or $\leq$ -0.4) as a strong correlation between any two attributes. This constraint is based on a study by Diesing [28], which recommends a minimum correlation of 0.4 0.5. The selected attributes with error values ($\geq$ 0.4 or $\leq$ -0.4) were not unique, but duplicate attributes existed. Of the duplicated attributes selected with the highest correlation value, so in the end, we obtained as many as 35 attributes. This resulted in an additional dataset $D_{corr}$ (35 attributes), which contains only strongly correlated features.

Each dataset, that is, $D_{all}$, $D_{scal}$, $D_{bw}$, and $D_{corr}$, was pro-

cessed using different data pre-processing scaling techniques, including MinMax, Standard, Robust, and without scaling (none). For each dataset with or without scaling techniques, Randomized Search [29] was employed to optimize the hyperparameters of each of the 14 classification algorithms. Cross-validation was performed using five-fold cross-validation for each validation and testing phase.

For each dataset, before entering the process of building a classification model using the 14 classification algorithms, training and testing sets were formed. From the 200 sets of metrics, we divided the dataset into 80% (160 data points) for training and 20% (40 data points) for testing. We split the datasets for training and testing using the `train_test_split()` function with the stratification parameter to maintain the proportion of classes in the training and testing sets.

The 14 classification algorithms can be broadly categorized based on their underlying approach. Tree-based models, including Random Forest (RF) [30] and Decision Tree (D3) [31] models, are known for their ability to handle nonlinearity in data without requiring feature scaling. Distance-based models, such as k-Nearest Neighbors (KNN) [32] and Support Vector Classifier (SVC) [33], rely heavily on the measurement of feature distances, making them particularly sensitive to scaling transformations. Probabilistic classifiers, including Gaussian Naïve Bayes with Isotonic Calibration (GNB-Isotonic), Gaussian Naïve Bayes with Sigmoid Calibration (GNB-Sigmoid), and Gaussian Naïve Bayes (NB) [34], [35] function under the assumption of feature independence and may benefit from certain types of pre-processing. Linear models, such as Logistic Regression (LogReg) [36], Linear Discriminant Analysis (LDA) [37], [38], Perceptron [39], Perceptron optimization based on Stochastic Gradient Descent (SGD) [39, p. 43-46], and Passive-Aggressive Classifier (PA) [40], assume linear relationships between features and classes and typically require scaling to enhance numerical stability. Bayesian and quadratic models, such as Quadratic Discriminant Analysis (QDA) [41]. Finally, neural network-based methods, such as Multi-Layer Perceptron (MLP) [42], rely on gradient-based optimization, which is highly sensitive to feature magnitudes.

The execution of the Randomized Search for each algorithm was repeated 30 times. Using 30 iterations in a Randomized Search provides a pragmatic balance between computational efficiency, a thorough exploration of the hyperparameter space, and model robustness. This implementation ensured that the best-performing model was selected without incurring excessive computational costs, thus making it a well-justified approach for this classification experiment.

The flowchart (in Fig. 2) illustrates a structured approach for training and selecting an optimal classification model using Randomized Search. The process began by splitting the dataset into 80% training and 20% testing to ensure that unbiased evaluation. Both subsets underwent a scaling transformation to standardize the feature magnitudes, thereby enhancing the model performance. A diverse set of classification algorithms—including SVM, Logistic Regression, k-NN, LDA, QDA, Gaussian Naïve Bayes, Decision Trees, MLP, Random Forest, Perceptron, SGD, and Passive Aggressive classifiers— was prepared for evaluation, employing 5-fold cross-validation to ensure robust assessment. An iterative loop

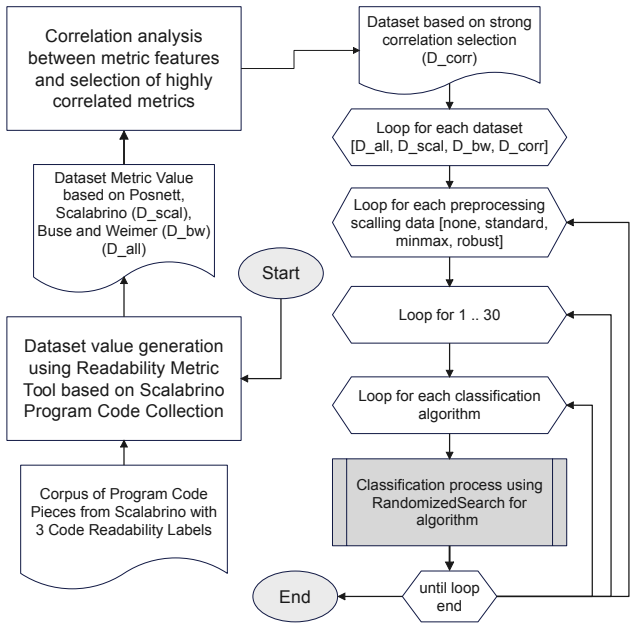


Fig. 1. The process flow for testing the 3 readability class classification.

executes Randomized Search for each classifier to optimize the hyperparameters efficiently.

Following training, cross-validation scores were measured to assess the generalization ability of the model and detect potential overfitting. Overfitting detection was performed to determine whether the best model generated by the algorithms was overfitted. This study implemented a quantitative method to assess whether a trained machine learning model overfits by comparing its performance on cross-validation and test data. Eq. (1) shows the conditions for detecting overfitting by using the quantitative method applied in this study.

$$\frac{|\text{mean\_cv\_score} - \text{mean\_test\_score}|}{\text{mean\_cv\_score}} > 0.10 \qquad (1)$$

The if condition in the given overfitting condition establishes a threshold-based criterion for detecting overfitting in the trained classification model. It evaluates the relative difference between the mean cross-validation score (mean_cv_score) and test score (test_score). Specifically, the condition checks whether the absolute difference between these scores, normalized by the mean cross-validation score, exceeds 10% (0.10). If this condition holds, the model is considered overfitting, indicating that it performs significantly better on the training data during cross-validation than on the independent test set, suggesting poor generalization. Conversely, if the relative difference remains within the 10% threshold, the model is deemed not to overfit, implying a balanced performance between the training and testing phases. This approach provides a quantitative measure for assessing the generalization ability of a model beyond the training dataset.

The best-performing model, determined based on the cross-validation performance, was then tested on the scaled testing dataset for the final validation. The selected model represents the most effective classification approach for a given dataset,

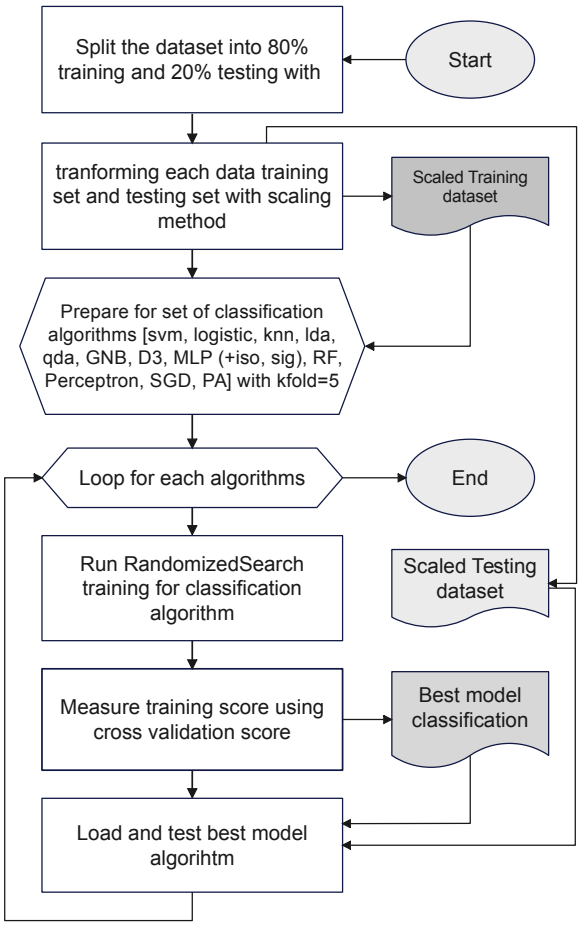


Fig. 2. The process flow for classification process with parameter optimization.

ensuring optimized accuracy and reliability in classification tasks. This workflow establishes a reproducible methodology for systematic machine learning model selection and evaluation.

## IV. Result and Discussion

### A. Classification Performance Results

After performing 30 iterations of the classification process for each of the 14 classification algorithms using Randomized Search across four datasets ($D_{all}$, $D_{scal}$, $D_{bw}$, and $D_{corr}$) with four different scaling configurations (without scaling, standard, min-max, and robust), the average accuracy and weighted F1-score were computed. An analysis was conducted to determine whether the classification model exhibited overfitting by evaluating the difference between the average cross-validation score and the test accuracy for each iteration.

In this study, the best average accuracy was obtained when the overfitting ratio did not exceed 6.67% (i.e., no more than two overfitting occurrences out of 30 iterations). For instance, in the case of the GNB-Isolate method, the best average accuracy was chosen as 0.53 with an overfitting ratio of 0% when using MinMax Scaling, rather than an average accuracy of 0.6 with an overfitting ratio of 100% when using Standard Scaling. Table II presents the results of the selection of the highest average accuracy while ensuring compliance with the overfitting threshold. Fig. 3 presents the optimal average accuracy of 14 classification algorithms under different data-scaling techniques: MinMax, Standard, Robust, and no scaling (none). The performance of each method is depicted using bar plots, in which the highest accuracy values for each classifier are highlighted numerically above the respective bars.

The exploration of 14 classification algorithms optimized using a Randomized Search revealed that the dataset $D_{corr}$ serves as the most optimal alternative for multiclass code readability classification. The $D_{corr}$ dataset comprises a selected set of combined metric features derived from the correlation analysis among the Scalabrino, BW, and Posnett metric groups. Based on the classification results, it can be inferred that the 48 combined metrics could be effectively represented by 35 attributes (approximately 73%).

By analyzing the best average accuracy across all classification algorithms, the dataset distribution based on scaling configurations indicated that $D_{corr}$ contributed to 42.86% (six algorithms) of the best accuracy results among the 14 classification algorithms, followed by $D_{bw}$ at 35.71%, $D_{all}$ at 14.29%, and $D_{scal}$ at 7.14%. However, when factoring in the overfitting constraint, where only one to two occurrences of overfitting are acceptable within 30 iterations, certain algorithms, including MLP, Perceptron, D3, SGD, and PA, cannot be considered optimal for multiclass classification tasks. These algorithms exhibit an overfitting rate exceeding 10% across all scaling configurations, making them less reliable for generalization.

After eliminating these five suboptimal algorithms, the dominance of the $D_{corr}$ dataset in representing the code readability metrics for multiclass classification became even more pronounced, accounting for 35.71% (five algorithms) of the best accuracy results among the remaining classification algorithms. The classifiers that achieve the most optimal performance using the $D_{corr}$ dataset are Random Forest (RF), Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Gaussian Naïve Bayes with Isotonic Calibration (GNB-Isotonic), and Quadratic Discriminant Analysis (QDA).

Dataset $D_{corr}$ demonstrates that the selection of measurement metrics based on correlated yet relevant attributes can be leveraged optimally using tree- and distance-based classification algorithms. The performance of the Random Forest algorithm (a tree-based model) is particularly effective when applied to datasets in which features exhibit strong correlations with one or more other features. These findings highlight the necessity of considering relevant correlations, whether positive or negative, between readability metrics when constructing a comprehensive set of code-readability metrics. Similarly, the characteristics of distance-based classification algorithms include Support Vector Classification (SVC) (although not entirely distance-based) and k-nearest neighbors (KNN) (which are fully distance-based), allow them to effectively utilize the $D_{corr}$ dataset.

The average classification accuracy of RF, SVC, and kNN significantly benefits from the application of dataset scaling on $D_{corr}$, particularly with MinMax and Robust scaling. This finding also highlights that the application of scaling techniques can help mitigate the risk of overfitting during

TABLE II. BEST AVERAGE ACCURACY IN MULTICLASS CLASSIFICATION OF CODE READABILITY

| Methods | Minmax | | | Standard | | | Robust | | | None | | | Best | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Acc | % Over | Data | Acc | % Over | Data | Acc | % Over | Data | Acc | % Over | Data | Acc | Data |
| RF | **0.611** | 3.33% | $D_{corr}$ | 0.607 | 6.67% | $D_{corr}$ | 0.601 | 3.33% | $D_{corr}$ | 0.609 | 3.33% | $D_{corr}$ | **0.611** | $D_{corr}$ |
| SVC | **0.590** | 0% | $D_{corr}$ | 0.528 | 10% | $D_{all}$ | 0.565 | 0% | $D_{corr}$ | 0.550 | 0% | $D_{all}$ | **0.590** | $D_{corr}$ |
| KNN | 0.553 | 43.33% | $D_{all}$ | 0.540 | 53% | $D_{all}$ | **0.572** | 0% | $D_{corr}$ | 0.498 | 56.67% | $D_{scal}$ | 0.572 | $D_{corr}$ |
| GNB-Isotonic | **0.570** | 0% | $D_{corr}$ | 0.530 | 100% | $D_{scal}$ | 0.550 | 0% | $D_{corr}$ | 0.550 | 0% | $D_{corr}$ | 0.570 | $D_{corr}$ |
| QDA | 0.500 | 0% | $D_{scal}$ | 0.570 | 0% | $D_{scal}$ | 0.550 | 0% | $D_{corr}$ | **0.570** | 0% | $D_{corr}$ | 0.570 | $D_{corr}$ |
| LogReg | 0.552 | 46.67% | $D_{bw}$ | 0.536 | 20% | $D_{bw}$ | 0.550 | 100% | $D_{bw}$ | **0.554** | 6.67% | $D_{bw}$ | 0.554 | $D_{bw}$ |
| MLP | 0.536 | 33.33% | $D_{bw}$ | 0.532 | 40% | $D_{all}$ | **0.548** | 10% | $D_{all}$ | 0.528 | 73.33% | $D_{bw}$ | 0.548 | $D_{all}$ |
| Perceptron | 0.531 | 56.67% | $D_{bw}$ | 0.492 | 26.67% | $D_{bw}$ | **0.541** | 60% | $D_{bw}$ | 0.506 | 20% | $D_{scal}$ | 0.541 | $D_{bw}$ |
| D3 | **0.531** | 16.67% | $D_{bw}$ | 0.524 | 20% | $D_{bw}$ | 0.525 | 33.33% | $D_{bw}$ | 0.517 | 6.67% | $D_{bw}$ | 0.531 | $D_{bw}$ |
| GNB-Sigmoid | **0.530** | 0% | $D_{scal}$ | 0.500 | 100% | $D_{all}$ | 0.470 | 0% | $D_{corr}$ | 0.500 | 0% | $D_{corr}$ | 0.530 | $D_{scal}$ |
| LDA | **0.530** | 0% | $D_{bw}$ | 0.530 | 0% | $D_{bw}$ | 0.530 | 0% | $D_{bw}$ | 0.530 | 0% | $D_{bw}$ | 0.530 | $D_{bw}$ |
| SGD | 0.521 | 20% | $D_{bw}$ | **0.525** | 33.33% | $D_{bw}$ | 0.520 | 46.67% | $D_{bw}$ | 0.474 | 33.33% | $D_{bw}$ | 0.525 | $D_{bw}$ |
| PA | 0.493 | 30% | $D_{bw}$ | **0.506** | 43.33% | $D_{corr}$ | 0.492 | 23.33% | $D_{all}$ | 0.447 | 30% | $D_{scal}$ | 0.506 | $D_{corr}$ |
| NB | 0.420 | 0% | $D_{corr}$ | 0.400 | 0% | $D_{corr}$ | **0.450** | 0% | $D_{all}$ | 0.420 | 0% | $D_{corr}$ | 0.450 | $D_{all}$ |

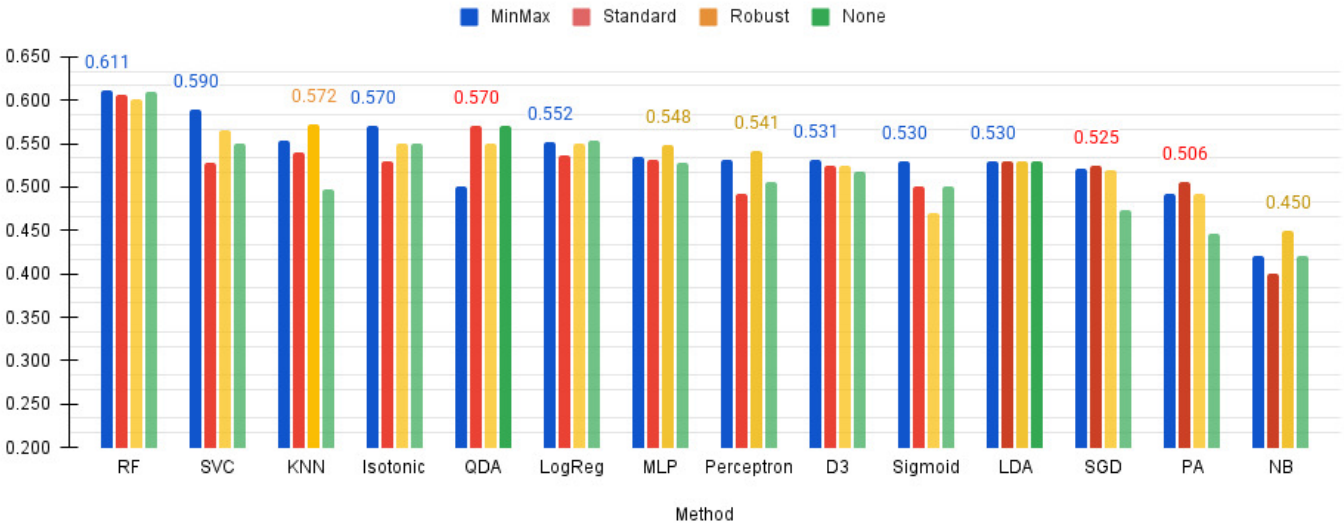


Fig. 3. Best average accuracy results for multiclass code readability classification (k-fold = 5).

multiclass classification model development. However, not all multiclass classification algorithms perform optimally even when utilizing $D_{corr}$ with scaling. In this study, the Passive-Aggressive (PA) algorithm exemplifies this limitation. Because the PA is inherently designed for binary classification, its performance in multiclass classification is suboptimal. This is evident from the fact that 43.3% of the classification models generated over 30 iterations using the PA exhibited overfitting.

In addition to dataset $D_{corr}$, the use of dataset $D_{bw}$, which consists of metric features defined by Buse and Weimer [4], does not yield an optimal performance in multiclass code readability classification. The highest average accuracy achieved was 55.4% using the Logistic Regression algorithm without data scaling and 53% using the Linear Discriminant Analysis (LDA) algorithm. By aligning the average accuracy results with the overfitting percentage from 30 iterations of model training, both the Logistic Regression and LDA demonstrated the ability to produce multiclass classification models with an acceptable level of overfitting. These findings suggest that the $D_{bw}$ dataset is more suitable for classification models in which the decision boundary formulation is based on a linear function. Conversely, the Perceptron, Decision Tree (D3), and Stochastic Gradient Descent (SGD) algorithms failed to achieve optimal performance, as this exploration indicates that all three algorithms exhibit an overfitting rate exceeding 6.67%.

Dataset $D_{all}$ contains the largest number of metric features, as it integrates the metrics proposed by Scalabrino, Buse, and Weimer (BW) and Posnett. Among the evaluated multiclass classification algorithms, multilayer perceptron (MLP) and Gaussian Naïve Bayes (NB) demonstrated the most optimal utilization of this dataset. The optimization of the average accuracy of these algorithms is primarily influenced by the application of Robust scaling to $D_{all}$. However, the average accuracy of MLP did not fully satisfy the overfitting threshold of less than 6.67% because three iterations still exhibited overfitting. Conversely, the NB algorithm achieved an accuracy of 0.45 on $D_{all}$, making it the least effective among the evaluated algorithms. The fourth dataset, $D_{scal}$, comprised 20 readability metrics derived from the model proposed by Scalabrino et al. [5]. The only classification algorithm that effectively utilizes this dataset is the Gaussian Naïve Bayes with a sigmoid activation function (GNB-sigmoid), particularly when MinMax scaling is applied. The results from 30 classification trials using

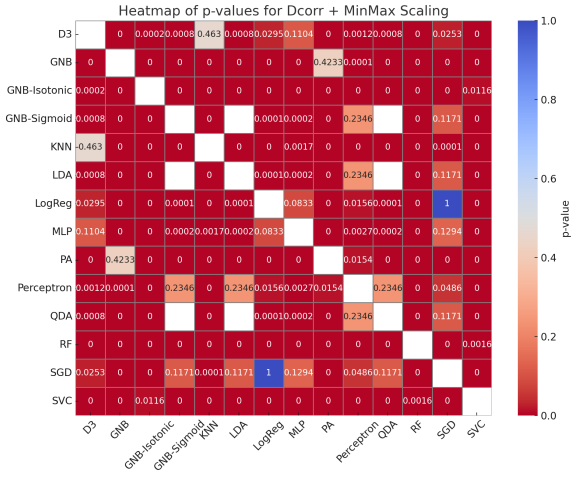


Fig. 4. Heatmap of p-Values for $D_{corr}$ with minmax scaling.

GNB-Sigmoid showed no signs of overfitting, regardless of whether MinMax, Robust, or scaling was applied.

The average accuracy results obtained by utilizing the dataset with various scaling configurations, as presented in Table II, highlight the significance of data scaling in influencing a dataset. Scaling serves as a crucial pre-processing step before building a multiclass classification model for code readability. However, the findings of this study indicate that the impact of scaling is not consistently definitive in yielding superior average accuracy. The effectiveness of scaling techniques depends on the classification model employed. Specifically, MinMax scaling was optimally utilized by the RF, SVC, GNB-isotonic, GNB-sigmoid, and LDA algorithms. Meanwhile, Standard scaling enhances the performance of QDA without causing overfitting. Although Robust scaling can be beneficial, it can lead to overfitting in some cases. The KNN and NB algorithms can leverage Robust scaling to optimize their performance without overfitting. These findings underscore the importance of selecting an appropriate scaling strategy that aligns with the fundamental assumptions of classifiers and their sensitivity to the distribution of metric-based dataset features, particularly for code readability in multiclass classification.

As part of the validation stage, in addition to applying rule-based overfitting checking and 5-fold cross validation, this study also conducted Statistical Significance Testing (Shapiro-Wilk test, paired t-test, or Wilcoxon singed-rank test) to validate the superiority of the selected models. Fig. 4 shows the p-value heatmap of the significance test results between the algorithms in the best configuration, namely $D_{corr}$ with MinMax scaling. Based on the p-value heatmap, it can be stated that Random Forest is consistently superior to the other algorithms because it shows a truly significant difference, not by chance.

Based on the accuracy of the results, several key findings answered the first research question (RQ1). Random Forest (RF) is the best-performing classification method for multiclass code readability classification, as it achieves the highest accuracy across most datasets and remains stable across different scaling techniques. SVC also performs well but is more sensitive to feature scaling, with MinMax scaling being the most beneficial. These findings suggest that ensemble methods such as Random Forest are more effective for code readability multiclass classification, particularly when feature selection is applied (as in $D_{corr}$).

Overall, dataset analysis underscores the importance of choosing the correct data pre-processing strategy based on the nature of the classifier. Feature correlation ($D_{corr}$) appears to enhance the accuracy of tree- and distance-based models, whereas balanced weighting ($D_{bw}$) benefits linear models. Complete feature sets ($D_{all}$) are favorable for neural networks and probabilistic models, whereas scaling transformations ($D_{scal}$) offer a limited but occasionally beneficial effect on certain classifiers.

### B. Attribute Role Analysis Based on Importance Score

This section outlines the process of analyzing the contribution of attributes (features) from the $D_{corr}$ dataset, which are critical for classifying source code readability into three classes. The analysis was conducted using the correlated dataset $D_{corr}$ with MinMax scaling and the Random Forest classification model because this configuration demonstrated the highest accuracy in the conducted trials. The $D_{corr}$ dataset comprises 35 attributes derived from the combined features proposed by Scalabrino, Buse-Weimer (BW), and Posnett.

Attribute contribution analysis was performed by computing the average `importance_mean` for each attribute exclusively in the $D_{corr}$ dataset. The classification model that achieved the highest performance, which employed $D_{corr}$ with MinMax scaling, was evaluated using the test data generated during the classification assessment process. The attribute importance weights were computed using the `permutation_importance` function from the `sklearn.inspection`. Attribute selection is based on the average importance score (mean_threshold) and standard deviation (std_threshold) of the highest `importance_mean` values, with selection criteria determined by predefined thresholds: a minimum average error threshold of [0.005, 0.01, and 0.02] and a maximum standard deviation error threshold of [0.015, 0.02]. The average (mean) was used to determine the overall contribution of the features (attributes) to the model performance based on 30 iterations. An average value greater than zero ($> 0$) indicates that the attribute consistently positively contributes to model performance. Conversely, if the average is approximately zero ($\approx 0$), then the attribute is likely to be irrelevant.

Similarly, if the average is negative ($< 0$), the attribute is likely to negatively impact the model performance. In addition to the mean threshold, the standard deviation of the `permutation_importance` values was considered. The standard deviation measures the variation (spread) in an attribute's importance score across the iterations. This variation reflects the consistency of the impact of the features on the model performance. A low standard deviation indicates that the contribution of the feature remained stable across all 30 iterations, whereas a high standard deviation suggests that the importance of the attribute is inconsistent, implying that its influence may vary, at times being beneficial, unimportant, or even detrimental.

TABLE III. AVERAGE BEST ACCURACY OF MULTICLASS CLASSIFICATION USING $Ds_1$, $Ds_2$, $Ds_3$, $Ds_4$, $Ds_5$, AND $Ds_6$

| Method | Avg Accuracy | Overfitting % | Dataset | Scaling |
|---|---|---|---|---|
| LDA | 0.550 | 0.0% | $Ds_4$ | MinMax |
| | 0.550 | 0.0% | $Ds_4$ | Standard |
| | 0.550 | 0.0% | $Ds_4$ | Robust |
| | 0.550 | 0.0% | $Ds_4$ | None |
| **RF** | **0.583** | **0.0%** | $Ds_6$ | **Robust** |
| **KNN** | **0.590** | **0.0%** | $Ds_2$ | **Robust** |
| SVC | 0.517 | 0.0% | $Ds_1$ | MinMax |
| | 0.545 | 0.0% | $Ds_3$ | Standard |
| | 0.579 | 0.0% | $Ds_5$ | Standard |

The next step involved constructing a dataset in which $D_{corr}$ served as the baseline, with attributes selected based on predefined thresholds. Attribute selection was performed according to threshold conditions for the mean and standard deviation, resulting in six distinct attribute groups. For each of these groups, a corresponding dataset was derived from the source dataset $D_{corr}$. Consequently, six new datasets were generated, each based on different attribute selections: $Ds_1$ (11 attributes), $Ds_2$ (22 attributes), $Ds_3$ (8 attributes), $Ds_4$ (17 attributes), $Ds_5$ (16 attributes), and $Ds_6$ (27 attributes).

Each dataset formed through this selection process was subsequently subjected to classification trials along with similar trials conducted for the $D_{all}$, $D_{scal}$, $D_{bw}$, and $D_{corr}$ datasets. The primary objective of these tests was to identify the attributes from $D_{corr}$ that contributed the most significantly to the best classification accuracy, thereby providing a foundation for developing alternative attributes or metrics for program code readability models. In addition, this analysis aimed to evaluate whether the six datasets resulting from attribute selection produced better classification performance than the $D_{all}$, $D_{scal}$, $D_{bw}$, and $D_{corr}$ models.

The best-performing models were selected based on an overfitting threshold $\leq$ 6.67% across 30 iterations for each dataset. The selection results, as shown in Table III, indicate that the K-Nearest Neighbors (KNN) algorithm achieves the best performance when applied to the $Ds_2$ dataset compared to other datasets. KNN achieved the highest average accuracy (59%), followed by Random Forest (RF) at 58.3%, Support Vector Classifier (SVC) at 57.9%, and Linear Discriminant Analysis (LDA) at 55%. The $Ds_2$ dataset (containing 22 metric attributes) is better suited for instance-based learning algorithms, such as KNN, whereas $Ds_6$ (27 attributes) is more effective for decision tree-based algorithms, particularly Random Forest. However, the highest average performance results obtained from these six newly formed datasets remained suboptimal compared with those achieved with the original $D_{corr}$ dataset.

The primary objective of the classification experiment using the six datasets, $Ds_1$, $Ds_2$, $Ds_3$, $Ds_4$, $Ds_5$, and $Ds_6$, was to identify which set of feature attributes (metrics) played a significant role in classification. Based on the results of this study, 22 feature attributes from dataset $Ds_2$ were identified as key metrics for measuring code readability. Table IV provides a detailed overview of the 22 feature attributes in the program code, including their corresponding metric categories.

By selecting 22 readability metric features from the feature set in dataset $D_{corr}$, this finding also addressed the second research question (RQ2). Among the Scalabrino metrics, eight key metrics play a significant role in multiclass code readability classification. For the Buse and Weimer metrics, 12 features were identified as being important for multiclass classification. Based on Posnett's metrics, two features were found to contribute significantly to the code readability classification experiment. Thus, based on the results of the multiclass code readability classification, it can be concluded that comment text readability, code complexity and structure, syntax and formatting, identifier naming and token usage, and code size and density are crucial factors in classifying Java source code into three readability categories: unreadable, neutral, and readable.

### C. Discussion

The performance results of multiclass classification based on 14 machine learning algorithms, although not optimal, show that the utilization of the definition of the code readability metric feature set, particularly the result of selecting features based on their correlation, can still be an alternative in multiclass classification of code readability. This study offers a practical and interpretable alternative based on the code readability metric features used in classification compared with the application of deep learning. Deep learning often requires significant computational resources and lacks transparency. The establishment of a feature metric based on the correlation result $D_{corr}$ that can be utilized by Random Forest to produce consistent performance can still be used to explain the model through the importance of the code readability feature. This makes machine learning based on metric features more suitable for applications that require interpretation and positions the machine learning framework as a complementary method to more complex deep learning approaches.

The different average accuracy performance results among the dataset definitions $D_{all}$, $D_{scal}$, $D_{bw}$, and $D_{corr}$ can be explained by variations in feature composition and selection strategies. $D_{all}$ integrates features from Scalabrino, Buse-Weimer, and Posnett, offering broader coverage but potential redundancy. In contrast, $D_{scal}$ and $D_{bw}$ focused on defining a specific set of metric features according to their respective models. By contrast, $D_{corr}$, which is formed from a correlation-based selection of $D_{all}$, can be said to be a metric feature selection that minimizes redundancy and retains only highly relevant features.

These differences affect the performance of the 14 machine learning classification algorithms. For example, tree-based models, such as Random Forest with $D_{corr}$, can effectively handle correlated features. Distance-based models, such as SVC and KNN, also perform well on $D_{corr}$ when proper scaling (e.g., MinMax, Robust) is applied because distance-based model algorithms are sensitive to feature magnitude and distribution. Linear models such as Logistic Regression and LDA showed better performance against $D_{bw}$ utilization, which seems to be more in line with the linear separability assumption. Probabilistic models, such as the calibrated Gaussian Naïve Bayes, perform reasonably well with $D_{scal}$ and $D_{corr}$ when scaling is used to reduce the risk of overfitting.

To optimize the readability interpretation based on the Scalabrino, Buse-Weimer, and Posnett readability metric fea-

TABLE IV. 22 SELECTED "CODE READABILITY" METRICS

| Metric | Category | Source |
|---|---|---|
| Scalabrino.commented_words_average | Comment and Text-Based Readability | Scalabrino |
| Scalabrino.synonym_commented_words_average | | |
| Scalabrino.synonym_commented_words_maximum | | |
| Scalabrino.comments_readability | | |
| Scalabrino.semantic_text_coherence_standard | | |
| Scalabrino.expression_complexity_average | Code Complexity and Structure | |
| Scalabrino.method_chains_average | | |
| Scalabrino.method_chains_maximum | | |
| BW.commas_average | Syntax and Formatting | Buse & Weimer |
| BW.indentation_average | | |
| BW.periods_average | | |
| BW.spaces_average | | |
| BW.indentation_maximum | | |
| BW.comments_average | Identifiers and Token-Based Complexity | |
| BW.identifiers_length_average | | |
| BW.number_of_identifiers_average | | |
| BW.number_of_identifiers_maximum | | |
| BW.numbers_maximum | | |
| BW.char_maximum | | |
| BW.words_maximum | | |
| Posnett.volume | Code Size and Information Theory | Posnett |
| Posnett.lines | | |

tures, in this study, feature selection based on the permutation importance method was performed on the best Random Forest model applied to $D_{corr}$ dataset with MinMax scaling. The results of the selection form six combinations of metric features, and then choose which combination is the best based on multiclass classification tests on each of the six combinations of features. Of the 35 features available from $D_{corr}$, 22 metric features were selected because they provided consistent positive contributions and low variance in the average accuracy of the multiclass classification model. These features included comment readability, code complexity, syntax, identifier naming, and information density.

## V. CONCLUSION

A multiclass classification study for machine learning-based code readability was conducted by utilizing metric feature definitions from the Scalabrino, Buse and Weimer, and Posnett models. Utilization of soft AutoML hyperparameter tuning, namely Randomized Search, produced an optimal multiclass classification model based on 200 Java codes from Scalabrino et al. The set with 35 metric features resulting from correlation-based future selection (forming the $D_{corr}$ dataset) consistently exhibited the highest average accuracy and a weighted F1 score. The Random Forest algorithm provides the highest average accuracy among the algorithms with or without utilizing MinMax, Standard, and Robust scaling transformation techniques on the data of each readability label with minimal overfitting conditions. The validity test based on Statistical Significance Testing of the classification performance results also shows that the RF algorithm is consistently and significantly superior to the other classification algorithms.

In this study, the most important feature metric was extracted using a permutation importance function based on the results of the previous best classification model. From the resulting six combinations, 22 out of 35 $D_{corr}$ metric features play an important role in the multiclass classification of code readability. Metric features include comment readability, code complexity, syntax, naming, and density. Overall, the average multiclass classification accuracy results generated in this study could not surpass the 72.5% accuracy of the GNN model proposed by Mi et al. Thus, in future research, it will be necessary to refine the definition of code readability metric features to better represent the code readability metric. In addition, the utilization of hybrid machine learning methods for multiclass classification of code readability can be explored to obtain better performance than the application of machine learning algorithms.

## AUTHORS' CONTRIBUTIONS

Conceptualization, BS, RF, TBA; methodology, BBS, RF, TBA; validation, BS; investigation, BS; resources, BS; data curation, BS; writing—original draft preparation, BS; writing—reviewing and editing, BS, RF, TBA; visualization, BS; supervision, RF, TBA; project administration, BS, RF, TBA; funding acquisition, RF, TBA.

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# Deep Learning-Based UI Design Analysis: Object Detection and Image Retrieval Using YOLOv8

Roba Alghamdi, Adel Ahmad, Fawaz alsaadi
Department of Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia

***Abstract*—Data-driven design models support various types of mobile application design, such as design search, promoting a better understanding of best practices and trends. Designing the well User Interface (UI) makes the application practical and easy to use and contributes significantly to the application's success. Therefore, searching for UI design examples helps gain inspiration and compare design alternatives. However, searching for relevant design examples from large-scale UI datasets is challenging and not easily stricken. The current search approaches rely on various input types, and most of them have limitations that affect their accuracy and performance. This research proposed a model that provides a fine-grained search for relevant UI design examples based on UI screen input. The proposed model will contain two phases. Object detection was implemented using the deep learning model 'YOLOv8', achieving 95% precision and 97% average precision. Image retrieval, leveraging the cosine similarity technique to retrieve the top 3 images similar to the input. These results highlight the system's effectiveness in accurately detecting and retrieving relevant UI elements, providing a valuable tool for UI designers.**

***Keywords*—Data-driven design; YOLOv8; design search; deep learning; user interface design**

## I. Introduction

Applications and mobile devices play a crucial role in the daily lives of individuals worldwide, facilitating a wide range of tasks, from simple calculations to more complex operations. Developers adhere to established guidelines and standards before releasing applications on digital marketplaces such as Apple's App Store and Google Play [1]. The development begins with defining requirements and designing the user interface, followed by creating mockups of the graphical user interface (GUI). UI/UX designers iteratively refine these mockups until a final design is achieved, which is then translated into a functional application. After undergoing rigorous testing, the application is released to users, emphasizing the increasing focus on mobile application quality [1].

The user interface (UI) is a fundamental element in determining the success of a mobile application, as it provides an interactive environment for users to engage with the software. The quality of UI design significantly influences user experience, acceptance, and overall app success [2]. In the highly competitive mobile application market, the UI design and app icons play a key role in differentiating an application from competitors, attracting downloads, minimizing user complaints, and enhancing retention rates. A well-designed UI balances visual appeal, efficiency, and ease of use, considering factors such as color harmony, layout organization, and overall design style [3].

Visual composition in UI design is a fundamental aspect of software development. The design process typically starts with wireframing based on user requirements and then structuring visual elements to ensure optimal interaction between the user and the application. Designers iteratively refine these wireframes by referencing existing online examples before applying high-fidelity visual effects, such as colors and typography, and incorporating relevant text and imagery [4].

Data-driven design models contribute to the development of mobile applications by predicting design performance and identifying the best practices and trends [5]. These models support various aspects of mobile application design, including interaction modeling, design search, and UI code generation. Recent advancements in machine learning and data analytics have significantly transformed UI design, allowing designers to explore extensive collections of UI designs based on specific criteria such as layout, color schemes, and functionality [5]. As technology advances, these tools will continue empowering designers to create innovative and user-centered UIs.

Leading mobile application marketplaces offer over six million applications, with projected revenue exceeding $935 billion by 2024—nearly twice the revenue generated in 2020 [6], [7]. The graphical user interface (GUI) is a core component of application success, serving as the interaction point between users and the application's functionalities. Well-designed GUIs go beyond aesthetics, improving usability and enhancing user satisfaction. With increasing competition in app marketplaces, creating engaging and intuitive interfaces has become a top priority for developers. However, designing high-quality GUIs remains challenging and labor-intensive, requiring extensive testing and iteration to ensure usability [8].

For novice and experienced designers, navigating the design space efficiently remains difficult. Seeking design examples has become essential for gaining inspiration and understanding UI trends for specific application functions. However, locating relevant examples within large-scale UI datasets is challenging due to the time-consuming nature of random searches, which may not provide accurate insights into modern UI trends, including layout options, visual components, and effects. An effective solution involves developing approaches that retrieve similar UI designs from large datasets using deep learning technologies. These methods transform GUI development by enabling efficient retrieval and comparison of visual components across extensive datasets [5].

Various studies have attempted to address the issue of UI design retrieval using different input methods such as keywords, sketches, wireframes, and UI images. Most existing studies rely on keyword-based input and often yield irrelevant examples due to mismatched user requirements. A more effective approach is needed to provide designers with practical examples that align with their needs. Research has

explored input-based image retrieval that considers UI content, hierarchical structure, and visual layout. However, current methods face challenges in performance, generalization, and applicability to diverse UI designs, affecting their accuracy and usability. For example, Swire [9] has a limitation in the approach performance because it retrieves irrelevant UI images that do not consider the UI content. The approach proposed by Deka et al. [6] retrieves similar results based on text and image content only.

In contrast, the approach of Liu et al. [10] limits the generalization and precludes the approach from working on any new unseen images because it relies on specified UI content. While others are limited in detecting small objects in UIs, such as icons and checkboxes, the VINS [11] approach restricted its application to specific UIs with a specified set of components. Detecting objects at different scales is challenging, particularly small objects. Data augmentation techniques are ways to solve the problem of detecting small objects on UI screens. These techniques are utilized to ensure the dataset does not lack sufficient training data or uneven class balance within the datasets and are adopted as an effective solution to improve the performance of object detection models. Many recent studies have shown that combining the YOLOv8 model with multiple data augmentation strategies led to significant improvements in accuracy and other performance metrics, as used in study [12]. Similar techniques were applied to improve the accuracy of brain tumor detection using MRI images, where data augmentation significantly increased brain tumor detection accuracy, improved the model's generalization ability, and reduced errors. This study confirms the effectiveness of data augmentation techniques in improving the performance of YOLOv8. This study highlights how to propose a practical model capable of efficiently detecting the most common UI components and retrieving UI images using deep learning and computer vision techniques. It also investigates the integration with custom data augmentation techniques to improve detection performance and address these limitations.

This research aims to overcome the limitations of previous methods by introducing a fine-grained UI search system that retrieves similar UI designs based on a given UI screen. The proposed system leverages deep learning techniques to help designers quickly understand design spaces, draw inspiration from existing applications, and enhance their UI designs to ensure application success. The primary objectives of this study include:

- Developing a model capable of retrieving relevant UI designs from large-scale datasets based on input images using deep learning and computer vision techniques.
- Improving accuracy in retrieving relevant UI examples by refining the search process to better align with designer needs.
- Evaluating the proposed model against the existing approach "VINS" to assess its effectiveness in enhancing the UI design retrieval process.

This study contributes to developing and evaluating a framework for fine-grained UI search. The YOLOv8 model was chosen for this study due to its architectural and technical improvements, which make it suitable for detecting user interface elements within images. Appreciation to its improved accuracy, faster performance, and ability to recognize objects of various sizes compared to previous versions, it can extract deeper and more effective features, making it the preferred choice, as demonstrated in this study [13]. YOLOv8 efficiently recognizes objects even in complex or diversely designed images, making it suitable for analyzing user interfaces containing multiple, closely spaced elements.

The proposed model integrates deep learning (YOLOv8) and computer vision techniques (Cosine Similarity) to effectively detect and retrieve highly similar UI designs with high precision. This work presents the first model that integrates these technologies within this domain, which makes it an advantage for this work. A new dataset was also created from the Rico dataset, incorporating preprocessing techniques and categorization into 21 classes—a novel contribution in this area. Data augmentation techniques were applied to ensure the dataset does not lack sufficient training data or uneven class balance within the datasets, resulting in 19,000 UI images. The proposed model surpasses the baseline model by 12% in UI image search accuracy [9]. This contribution highlights the proposed model's effectiveness and potential impact on advancing UI design research.

The rest of the paper is structured as follows: the "Related Work" in Section I examines previous studies, while the "Materials and Methods" in Section II describes the proposed methodology and dataset. The "Experiments" in Section III presents the experimental setup and findings. Lastly, the "Conclusion and Future Work" in Section IV highlights the principal results and suggests possible future research directions.

## II. Related Work

Various approaches have been proposed in UI design retrieval, utilizing different input types to enhance search efficiency and accuracy. Traditional keyword-based search methods have evolved into more advanced techniques, such as natural language queries, image-based searches, and deep learning-driven retrieval models. Studies have compared these methods based on usability, effectiveness, and retrieval accuracy, showcasing significant improvements with deep learning techniques. Cardenas et al. [5] introduced GUIGLE, a framework for GUI search that facilitates the conceptualization process for UI design. GUIGLE enables advanced searches using natural language queries, incorporating UI components, on-screen text, color schemes, and application names. The framework consists of three main components: data collection, quality filtering, and indexing, achieving a 68.8% retrieval relevance rate. Chen et al. [14] proposed Gallery D.C, a large-scale UI component gallery that leverages computer vision techniques and reverse engineering. This system categorizes 11 UI components across 25 Android application categories and provides search, comparison, and summarization tasks. It employs Faster R-CNN for UI element detection, demonstrating superior design sharing and information retrieval performance. The main limitation of using keywords is retrieving design examples with UI content and visual layout structure different from user requirements.

Beyond keyword-based searches, researchers have explored image-based retrieval using wireframes, sketches, and UI

screens as input methods, which are faster to specify and easier to learn than keywords. Huang et al. [9] developed Swire, a deep learning-based UI retrieval model trained on a large-scale UI sketch dataset. Swire utilizes VGG-A sub-networks to match UI screens with sketches, achieving a 60% accuracy rate for retrieving relevant UIs. Chen et al. [15] proposed a wireframe-based UI design search engine using deep learning. This approach includes reverse engineering to construct a large-scale UI dataset, encoding visual semantics with a CNN-based autoencoder, and employing KNN for UI design search. The evaluation results demonstrated superior performance compared to existing search methods that rely on different input types. The main drawback of these two models is that they return user interface designs that are generally similar to the query user interfaces, so they may miss some UI components or return irrelevant results. To solve this problem, examples of design that will help designers in practice must be found. Deka et al. [6] introduced the Rico dataset, the largest UI dataset to date, containing 72,219 UI screenshots from 9.7K Android applications across 27 categories. The dataset includes structural, textual, visual, and interactive UI properties, supporting deep learning applications for design retrieval. Rico's autoencoder-based UI layout similarity model demonstrated strong retrieval capabilities using text and image-based content only, which is considered a weakness. Liu et al. [10] extended the Rico dataset by introducing an automated approach for generating semantic annotations, identifying UI components' structural and functional roles. These annotations were applied to the 72,219 UI screens, enabling enhanced UI retrieval through autoencoder-based similarity searches. The model relies on a pre-defined hierarchy of UI content, so it does not work on any new, unseen images. Bunian et al. [11] proposed VINS, a visual search framework for retrieving UI design examples based on wireframes or UI screens. The framework integrates an object detection model using SSD for UI component identification and an attention-based autoencoder for image retrieval, achieving a mean average precision (mAP) of 76% for component detection and up to 90% precision in retrieving similar UI designs. This model's shortcoming is that it only detects 11 classes of UI components and is noticeably unable to detect small objects within the UI. The proposed model tried to solve these shortcomings by generalizing as much as possible to the most significant number of UI components, focusing on improving the detection of small components by applying some augmentation techniques and improving the model's performance to work on any input image.

Sun et al. [16] introduced a UI component recognition model using CNN techniques. The approach involved pre-processing UI images through grayscale conversion, noise removal, segmentation, and CNN-based classification into 14 UI component types. While effective, the model struggled with complex, user-defined UI components and misclassification of similar elements. Nguyen et al. [17] developed REMAUI, a reverse engineering framework for UI design analysis. The system detects UI components and generates static applications using computer vision, Optical Character Recognition (OCR), and mobile-specific heuristics. The primary limitation of this approach lies in its binary classification of UI elements, restricting its ability to distinguish between different component types. Moran et al. [18] proposed a machine learning-based prototype for GUI analysis in mobile applications, incorporating detection, classification, and assembly tasks. The detection phase employs computer vision techniques and OCR to identify GUI components, utilizing edge detection, dilation, and contour bounding boxes to refine object recognition. All of these approaches evaluate detection accuracy by a small number of GUIs.

CNN-based classification further enhances detection accuracy, outperforming previous GUI analysis methods. Recent advancements in deep learning have significantly improved object detection, image classification, and semantic segmentation for UI design retrieval. Faster R-CNN, employed in Gallery D.C, achieved a recall of 0.65, a precision of 0.73, and a mean average precision (mAP) of 0.69 at an Intersection over Union (IoU) threshold of 0.6. Meanwhile, SSD, used in VINS, demonstrated superior performance with an mAP of 76.39% and an Area Under the Curve (AUC) of 79.02% at IoU=0.5. The trade-off between two-stage detectors like Faster R-CNN, which yield higher accuracy but require substantial computational power, and one-stage detectors like YOLO and SSD, which are faster and more efficient for real-time mobile applications, remains a critical consideration in UI retrieval research. Since it is important to focus on performance efficiency in addition to speed, the Yolo model was adopted in the model proposed in this paper.

The Rico dataset, the largest in UI research with 72,000 images, requires refinement to remove duplicates caused by user interaction traces. Previous studies have used limited class annotations, restricting their applicability. While deep learning techniques have improved UI retrieval based on user preferences, challenges remain in performance, generalization, and adaptability. To overcome these issues, a YOLO-based model was proposed that enhances detection by re-annotating the Rico dataset into 21 classes, making UI retrieval more accurate and comprehensive.

## III. Materials and Methods

This section describes the methodology and architecture of the proposed fine-grained search system, designed to retrieve relevant UI design examples by integrating deep learning (DL) models. Fig. 1 illustrates the general methodology used in this system:

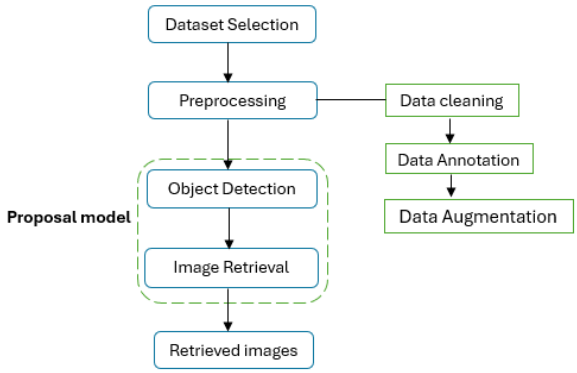


Fig. 1. The proposed system steps.

### A. Data Preprocessing

Data preprocessing is a crucial step in machine learning that ensures the dataset's quality, consistency, and usability. Leveraging the Rico dataset as the cornerstone of the research investigation, the researchers meticulously navigate through these preparatory stages to ensure the data's integrity, richness, and relevance. This process consists of three main steps: Data Cleaning, Data Annotation, and Data Augmentation, which refine the dataset for optimal model training.

*1) Data cleaning:* Since raw datasets often contain inconsistencies, redundant images, and noise, a systematic filtering process was applied to remove incomplete, irrelevant, or low-quality data. The Rico dataset, the largest dataset in UI research with 72,000 UI images, required refinement to eliminate duplicate images caused by user interaction traces. The filtering criteria included:

- Removing images with less than two UI components.
- Eliminating empty or non-English UI screens.
- Removing duplicate UI screens to avoid bias.

Fig. 2 shows examples of deleted images that did not meet the dataset's quality standards.

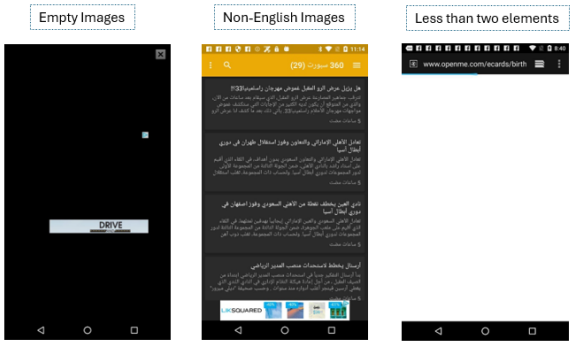


Fig. 2. Examples of deleted photos.

*2) Data annotation:* To ensure accurate and granular classification, the dataset was annotated into 21 distinct UI component classes using the Roboflow platform. These classes include BackgroundImage, BottomNavigation, Button, Card, Checkbox, Drawer, Edit Text, Icon, Image, Map, Modal, Multi Tabs, Page Indicator, Progress Bar, Radio Button, Seek Bar, Spinner, Switch, Text, Tool Bar, and Upper Task Bar. Each category was assigned a specific color to facilitate visual identification and improve model interpretability.

*3) Data augmentation:* Multiple augmentation techniques were applied to address class imbalance and enhance dataset diversity, leveraging the Roboflow platform. These included:

- Rotation
- Saturation adjustment
- Brightness modification
- Exposure correction
- Noise addition

This augmentation process tripled the number of instances in underrepresented classes, enhancing the trained model's robustness and generalization capability.

### B. Model Architecture

The main objective of this research is to build a fine-grained search model that retrieves similar UI designs depending on a given UI screen that fits the designer query and enhances the detection performance, especially for small objects such as icons, checkboxes, and others. Fig. 3 illustrates the architecture of the model. The proposed fine-grained search model consists of five main phases:

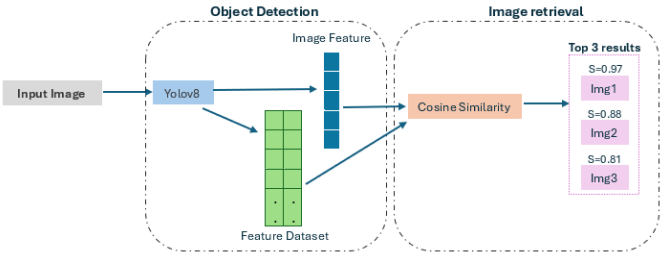


Fig. 3. Model architecture.

*1) Object detection:* Identifies UI components and their locations using the YOLOv8 [19] model. The YOLOv8 is one of the most advanced deep learning-based object detection models in current use, known for its high accuracy and rapid processing capabilities. The model uses convolutional layers to detect fine details like edges, shapes, and textures, dividing images into regions to identify and classify objects, such as vehicles, pedestrians, and animals, using bounding boxes and trained datasets [20]. The model processes images through the following steps:

- Resizing images to 640x640 pixels for input consistency.
- Normalizing pixel values to [0,1] range for stable neural network processing.
- Applying convolutional layers to extract shapes, edges, and textures.
- Generating bounding boxes with confidence scores to classify detected UI elements.

This methodology enhances model precision and detection speed, making it suitable for real-time UI retrieval applications.

*2) Feature extraction:* In computer vision, retrieving similar images based on extracted features is a powerful tool that enables applications ranging from automated tagging in media libraries to more complex uses in visual search engines and recommender systems. Extracts UI screen structure features and retrieves similar designs using cosine similarity. After detecting UI components, the YOLOv8 model generates feature vectors representing the spatial structure of each UI screen. Lower layers focus on basic elements, while deeper layers summarize complex structures, condensing these details into a global feature vector representing each image's content [21] [22]. These vectors encode:

- Bounding box coordinates (x, y, width, height).
- Class probabilities and confidence scores.

This feature vector acts as a numerical signature that reduces the complexity of images, allowing for more efficient and computationally manageable comparisons [23]. A global feature vector is derived by calculating the mean of all bounding boxes, creating a compact yet descriptive representation of the UI screen.

*3) Feature dataset construction:* Extracted feature vectors are stored in a structured database for efficient retrieval. This database transforms raw images into comparable vectors, streamlining retrieval without requiring direct pixel comparisons [24]. The indexing process ensures:

- Fast similarity comparisons across large UI datasets.
- Optimized storage using Python's Pickle serialization to avoid redundant computations.

This feature dataset enables the system to retrieve visually similar UI designs efficiently, supporting large-scale searches.

*4) Similarity-based image retrieval:* The model employs cosine similarity to retrieve images most similar to a query UI screen. This metric, which measures the cosine of the angle between two vectors, is advantageous as it focuses on the orientation of vectors rather than their magnitudes, making it suitable for high-dimensional data like feature vectors [25]. The similarity between two feature vectors $f_i$ and $f_q$ is calculated using the cosine similarity formula:

$$cosine_similarity(f_i, f_q) = \frac{f_i \cdot f_q}{\| f_i \| \| f_q \|} \quad (1)$$

Where $f_i \cdot f_q$ is the dot product, and $\|f_i\|\|f_q\|$ is the product of their magnitudes. Once similarity scores are computed, the system ranks images based on their cosine similarity scores, retrieving the top-k most similar UI designs [26]. This approach enhances retrieval accuracy and efficiency.

*5) Highlighting key regions in retrieved images:* To improve interpretability, retrieved UI images are highlighted with bounding boxes indicating significant regions the model detects. This visual emphasis helps users understand which UI elements contributed to the match.

- Bounding boxes are overlaid in distinct colors to enhance visibility.
- Solid-colored highlights (e.g., green rectangles) focus attention on key UI elements.

This method improves user experience and decision-making in UI retrieval applications.

### C. Dataset

The Rico dataset is a resource for mobile app design, containing design data from over 9,772 Android apps across 27 categories [6]. It includes over 72,000 unique UI screens, documenting interactive, textual, structural, and visual design elements. The dataset provides user interaction traces, app metadata from Google Play (category, ratings, downloads), and detailed UI components such as buttons, cards, text fields, and icons. It also includes XML annotation files, but for YOLOv8, these need to be converted into TXT files representing bounding boxes with class labels and coordinates. The dataset is cleaned and preprocessed, with 19,727 images classified into 21 categories, averaging 17 annotations per image.

## IV. Experiments and Results

Python was used as the primary programming language for the model's experiments due to its extensive support for machine learning and data science libraries. Python's flexibility and wide range of tools allowed us to implement the proposed methodologies efficiently. Given the computational limitations of the local machine, the Python code is executed using Google Colaboratory, a cloud-based platform that provides free GPU access [27].

Due to the large dataset size, the dataset was uploaded to the Kaggle platform which used its library to import and manage it. The Ultralytics library was employed to train the YOLOv8x model, while the sklearn.metrics. A pairwise package was utilized to implement cosine similarity in the image retrieval process. To optimize the proposed object detection model, the IoU (Intersection over Union) threshold is set to 0.7 and the confidence threshold to 0.25. Additionally, the input image size was resized to 700x700 pixels. These hyperparameters were chosen based on empirical experimentation to achieve the best trade-off between accuracy and performance.

### A. Data Preprocessing

Data preprocessing is a crucial step that ensures the dataset is optimized for model training. The preprocessing steps included:

- Data Cleaning: Removing noisy or irrelevant annotations
- Annotation Conversion: Transforming XML files into YOLO TXT format
- Data Augmentation: Enhancing dataset diversity and balancing class distribution

For augmentation, the Roboflow [28] utilized a pivotal platform within the realm of computer vision and machine learning. It offers a comprehensive suite of tools tailored to streamline the data preparation pipeline. Roboflow offers various augmentation techniques, including geometric transformations, color adjustments, and specialized augmentations. After augmentation, underrepresented classes saw a threefold increase in image samples, bringing the dataset size to 19,727 images. The final category distribution is shown in Table I.

### B. Model Training

The experiment leveraged the YOLOv8 [19] model for object detection to detect various elements within the research dataset. The training process was initiated with a pre-trained YOLOv8x model that utilized the robust capabilities of the Ultralytics framework. The Yolov8 had multiple versions with different parameters, speed, and mAP. The YOLOv8x was selected due to the large dataset and the importance of accuracy

TABLE I. DATASET CATEGORIES DISTRIBUTION

| Category | Train | Valid | Test | Sum |
|---|---|---|---|---|
| BackgroundImage | 1660 | 250 | 131 | 2041 |
| BottomNavigation | 1619 | 92 | 62 | 1773 |
| Button | 14042 | 2857 | 1603 | 18502 |
| Card | 5128 | 927 | 497 | 6552 |
| Checkbox | 3855 | 606 | 346 | 4807 |
| Drawer | 2063 | 212 | 131 | 2406 |
| EditText | 5032 | 954 | 570 | 6556 |
| Icon | 54602 | 10747 | 4873 | 70222 |
| Image | 20502 | 4429 | 1967 | 26898 |
| Map | 552 | 69 | 37 | 658 |
| Modal | 1466 | 239 | 146 | 1851 |
| MutilTabs | 2768 | 289 | 153 | 3210 |
| PageIndicator | 3070 | 112 | 110 | 3292 |
| ProgressBar | 698 | 24 | 33 | 755 |
| Radiobutton | 2112 | 458 | 272 | 2842 |
| SeekBar | 967 | 65 | 45 | 1077 |
| Spinner | 4952 | 708 | 517 | 6177 |
| Switch | 1135 | 165 | 161 | 1461 |
| Text | 116927 | 23407 | 11147 | 151481 |
| ToolBar | 8710 | 1825 | 823 | 11358 |
| UpperTaskBar | 13706 | 2762 | 1374 | 17842 |

over speed, the most robust version among the YOLOv8 models. The dataset was split into three subsets:

- 70% for training
- 20% for validation
- 10% for testing

This split allowed for efficient model training while preventing overfitting. The dataset was specified in a custom configuration file, and hyperparameter tuning was conducted to optimize model performance.

### C. Evaluation Metrics

For the proposed model, the Precision (P) and Average Precision (AP) are used as key metrics to evaluate the model:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

where: $TP$ (True Positives): Correctly detected objects. $FP$ (False Positives): Incorrectly detected objects. $FN$ (False Negatives): Missed objects.

The Mean Average Precision (mAP), a widely used metric for object detection tasks, was computed as follows:

$$mAP = \frac{\sum AP_n}{N} \tag{3}$$

where $AP_n$ represents the average precision for class $n$.

### D. Results

After training, the YOLOv8x model was tested on the validation set using a confidence threshold of 0.5, meaning only detections with a confidence score of 50% or higher were considered valid. This threshold was chosen to balance the results, reducing false positives while ensuring that true detections were not missed. The model achieved a 95% precision and a 97% average precision for the object detection component in all classes. Table II. presents the class-wise precision and AP values.

TABLE II. PRECISION AND MAP FOR EACH CLASS

| Class | P | mAP50 |
|---|---|---|
| BackgroundImage | 0.934 | 0.976 |
| BottomNavigation | 1 | 0.951 |
| Button | 0.968 | 0.983 |
| Card | 0.898 | 0.974 |
| Checkbox | 0.975 | 0.981 |
| Drawer | 0.97 | 0.991 |
| EditText | 0.921 | 0.96 |
| Icon | 0.96 | 0.969 |
| Image | 0.963 | 0.974 |
| Map | 0.939 | 0.988 |
| Modal | 0.951 | 0.994 |
| MutilTabs | 0.969 | 0.985 |
| PageIndicator | 0.929 | 0.983 |
| ProgressBar | 0.949 | 0.973 |
| Radiobutton | 0.987 | 0.986 |
| SeekBar | 0.968 | 0.945 |
| Spinner | 0.921 | 0.949 |
| Switch | 0.956 | 0.981 |
| Text | 0.951 | 0.973 |
| ToolBar | 0.954 | 0.976 |
| UpperTaskBar | 0.965 | 0.981 |
| ALL | 0.954 | 0.975 |

For image retrieval, the model successfully identified the three most similar UI designs to the input image using cosine similarity, displaying results as a ranked list of top-matching UIs. The colored bounding boxes in the second image represent each part of the UI query image, each color representing a different component. Fig. 4 shows an example of this step.

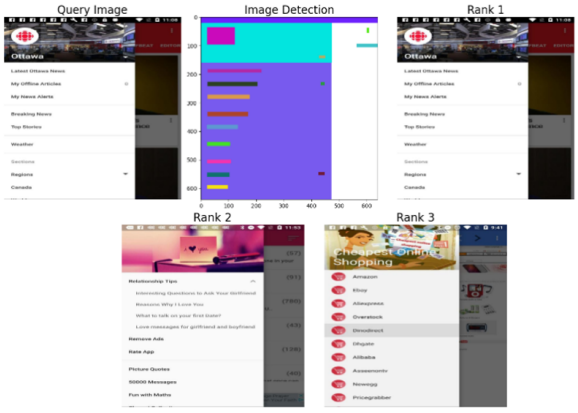


Fig. 4. The Retrieval results of out model.

### E. Comparison with Baseline Model

To highlight the improvements of the proposed model, a comparison with the baseline model VINS [9] was made, which combined the SSD model with Autoencoder to build the entire model. The proposed model relied on Yolov8 for feature detection, extraction, and storage and used Cosine similarity to retrieve images similar to the one given. At the same time, we relied on Yolov8 for feature detection, extraction, and storage and used Cosine similarity to retrieve similar images to the given one. Due to the unavailability of the model's source code, it was impossible to reapply the model to the dataset used in this research. Therefore, a rough comparison was made based on the mAP metric described in that study. However, it should be noted that the dataset used in this work is more extensive and diverse in terms of the number of classes. Although a direct comparison is not possible, the proposed system significantly outperforms VINS, achieving an mAP of 97% compared to VINS's 76.39% as a result reported in the literature [9], demonstrating superior accuracy and effectiveness in object detection and UI retrieval. This comparison is approximate and should be interpreted in the context of the different datasets and models used. The comparison results are presented in Table III.

TABLE III. COMPARISON WITH THE BASELINE MODEL

| Model | mAP50 | Technique used |
|---|---|---|
| VINS | 76.39% | SSD and Autoencoder |
| The proposed Model | 97% | Yolov8 and Cosine similarity |

## V. DISCUSSION

The results confirm the effectiveness of YOLOv8 in detecting UI elements. To determine the best version of Yolo models in the dataset, all versions were trained on the data and assigned an epoch value of 20 and a batch of 16. The results in Table IV indicate that YOLOv8x achieved the highest accuracy, making it the optimal choice for the dataset.

TABLE IV. VARIANCE MODELS RESULTS

| Model | Precision | mAP50 |
|---|---|---|
| YOLOv8n | 0.783 | 0.796 |
| YOLOv8s | 0.798 | 0.844 |
| YOLOv8m | 0.808 | 0.843 |
| YOLOv8l | 0.803 | 0.866 |
| YOLOv8x | 0.827 | 0.866 |

The proposed model successfully learns how to extract relevant features from images and then classifies and locates objects effectively across all images in the dataset. The model was trained on the Revised Rico data, and annotations were made on each image to identify the exact locations of objects within it based on the dataset categories. In addition, augmentation was performed on some under-representation classes to ensure the quality of the model and increase the chance of the model detecting these objects. The results of testing the proposed model using data extracted from the Rico dataset showed high performance in different categories, where the mAP reached 98% of overall categories, indicating that the model outperformed VINS [9] by about 20%. This is consistent with the results reported in the study [21], where the performance of their model also improved. However, the model still faces challenges predicting some categories, such as the "ProgressBar" and "SeekBar." This could be due to the imbalance of the data, which biases the model towards the higher-ranked categories. Even after trying to balance the dataset using a downsampling technique by removing images that collect objects from the majority class to achieve partial convergence with the rest of the classes and applying augmentation techniques to the minority class images, there was still a noticeable difference in the distribution of images between classes. These lower-ranked classes are often associated with some highly-ranked classes, which limits the possibility of creating balanced data.

Overall, this study demonstrates significant advancements in UI detection and retrieval, outperforming previous models and providing an effective tool for analyzing mobile UI designs.

## VI. CONCLUSION

In this study, we developed an object detection and image retrieval model leveraging the YOLOv8 framework and cosine similarity to analyze UI components. The dataset, sourced from the Rico dataset, was preprocessed, annotated, and augmented to enhance model performance. TThe hyperparameters were optimized through rigorous experimentation to achieve high precision and accuracy in detecting and classifying UI elements. The results demonstrated the effectiveness of the YOLOv8x model in object detection, outperforming the baseline VINS model by a significant margin. The proposed approach achieved an overall mean Average Precision (mAP) of 97%, compared to 76.39% for the VINS model, highlighting its robustness in accurately identifying UI components.

Additionally, the integration of cosine similarity facilitated efficient image retrieval, allowing the system to suggest visually and structurally similar UI designs. Despite the promising results, some challenges remain, particularly in predicting underrepresented UI components such as "ProgressBar" and "SeekBar." While augmentation and balancing techniques improved performance, disparities in category distribution persisted.

Future work could focus on further dataset balancing strategies, exploring alternative deep learning architectures, and refining feature extraction techniques to enhance retrieval accuracy. Expanding the dataset to include various UI designs from different platforms (e.g., iOS, web applications) and categories could enhance the system's versatility. The model can also be integrated with an Android app, making it easier for designers to leverage a variety of UI designs. The proposed approach represents a significant advancement in UI element detection and retrieval, offering a valuable tool for mobile UI designers and developers to analyze and refine interface layouts efficiently. The study underscores the potential of deep learning techniques in automating UI analysis, paving the way for more intelligent and adaptive design systems.

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# Adversarial Attack on Autonomous Ships Navigation Using K-Means Clustering and CAM

Ganesh Ingle, Kailas Patil, Sanjesh Pawale
Department of Computer Engineering, Vishwakarma University, Pune, India

***Abstract*—As Maritime Autonomous Surface Ships (MASSs) increasingly become part of global maritime operations, the reliability and security of their object detection systems have become a major concern. These systems, which play a crucial role in identifying small yet critical maritime objects such as buoys, vessels, and kayaks, are particularly susceptible to adversarial attacks, especially clean-label poisoning attacks. These attacks introduce subtle manipulations into training data without altering their true labels, thereby inducing misclassification during model inference and threatening navigational safety. The objective of this study is to evaluate the vulnerability of maritime object detection models to such attacks and to propose an integrated adversarial framework to expose and analyze these weaknesses. A novel attack method is developed using K-means clustering to segment similar object regions and Class Activation Mapping (CAM) to identify high-importance zones in image data. Adversarial perturbations are then applied within these zones to craft poisoned inputs that target the YOLOv5 object detection model. Experimental validation is performed using the Singapore Marine Dataset (SMD and SMD-Plus), and performance is measured under different perturbation intensities. The results reveal a considerable decline in detection accuracy—especially for small and mid-sized vessels—demonstrating the effectiveness of the attack and its capacity to remain imperceptible to human observers. This research highlights a critical gap in the security posture of AI-based navigation systems and emphasizes the urgent need to develop maritime-specific adversarial defense strategies for ensuring robust and resilient MASS deployment.**

***Keywords*—Maritime autonomous surface ships; object detection; clean-label poisoning attacks; adversarial attacks**

## I. Introduction

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly being deployed across critical domains such as healthcare, finance, defense, and autonomous transportation. In particular, the maritime industry has seen a transformative shift with the advent of Maritime Autonomous Surface Ships (MASSs), where AI-powered systems enable autonomous navigation, object detection, and situational awareness. The reliance of these systems on data-driven models, however, introduces new vectors for cyber-physical vulnerabilities, particularly those associated with training data integrity and model robustness.

Among the most significant threats to ML systems are data poisoning attacks, which involve the deliberate corruption of training data to manipulate model behavior. Such attacks can cause substantial performance degradation or induce specific, targeted misclassifications. While traditional data poisoning techniques typically involve altering both the features and labels of the training samples, recent work has highlighted the emergence of pure label poisoning attacks, wherein only the data is subtly manipulated while the labels remain unchanged (Turner et al., 2019; Saha et al., 2020). These attacks are particularly concerning because they can bypass standard data validation and noise detection protocols, making them harder to detect and mitigate.

The maritime domain presents a unique set of challenges for adversarial robustness. Object detection models used in MASSs must be capable of identifying small, dynamic, and often occluded objects such as buoys, small boats, and kayaks (Rekavandi et al., 2022; Shao et al., 2022). Misclassifying such objects due to adversarial manipulation can result in navigational errors with potentially severe consequences. Despite the growing use of deep learning models such as YOLOv5 for maritime object detection, current literature offers limited focus on adversarial risks specific to the maritime context. Most studies have concentrated on general adversarial attacks in image classification domains using datasets like CIFAR-10, ImageNet, or MNIST (Goodfellow et al., 2015; Madry et al., 2018), with minimal adaptation to marine scenarios and autonomous navigation systems.

This paper addresses this gap by proposing a novel adversarial attack framework tailored for maritime object detection systems, particularly those deployed in MASSs. The research objective is two-fold: (i) to demonstrate the feasibility and effectiveness of clean-label poisoning attacks in marine environments, and (ii) to develop an integrated methodology that leverages K-means clustering for unsupervised segmentation and Class Activation Mapping (CAM) for identifying high-saliency regions in the image space. By combining these techniques, the proposed method creates adversarial examples that are both functionally deceptive and visually imperceptible, targeting the YOLOv5 object detection model trained on the Singapore Marine Dataset (SMD and SMD-Plus). Data poisoning attacks pose a substantial threat to machine learning systems by exploiting vulnerabilities through the manipulation of training data, leading to erroneous predictions or decisions. Although advancements in machine learning have improved the detection of traditional data poisoning attacks, the rise of clean-label or pure label poisoning attacks—where input features are subtly altered without changing the labels—presents a more complex detection challenge [24]–[27], [30], [31].

These attacks typically follow a multi-stage process. First, attackers gather information about the target model and its training data from public datasets or distributionally similar sources [22], [25]. Then, during the poison sampling phase, specific instances are manipulated or synthetically generated to meet malicious objectives. In the manipulation phase, small but targeted perturbations are introduced to selected features. The tampered data is then injected into the training pipeline,

often by compromising data collection or storage systems [25], [27], [30], [31].

Retraining the model on this poisoned dataset can lead to performance degradation or targeted misclassifications. Attackers exploit the compromised model to induce incorrect behavior in downstream tasks [25], [27], [30].

To achieve this, the study employs a multi-stage process that includes dataset preprocessing, feature clustering, neural network training with CAM integration, perturbation injection, and retraining using poisoned data. The experiments are conducted under various levels of adversarial intensity, and the resulting impacts on model accuracy and misclassification rates are systematically evaluated. The findings reveal that even small perturbations focused on CAM-highlighted regions can cause the model to misidentify marine objects with high confidence, often without human-perceptible visual artifacts. In summary, this research makes three primary contributions: (1) it introduces a domain-specific adversarial attack strategy combining K-means and CAM; (2) it validates the vulnerability of deep learning-based maritime object detection models through experimental results; and (3) it provides actionable insights for future development of robust defense mechanisms tailored to maritime AI applications. To address these challenges, this paper presents a comprehensive methodology that integrates K-Means clustering and Class Activation Mapping (CAM) to generate clean-label poisoning attacks on object detection models within maritime environments. The remainder of this paper is structured as follows: Section II provides relevant background on MASS technologies and AI-driven object detection. Section III reviews related work in adversarial machine learning and maritime cybersecurity. Section IV introduces the core attack models and threat landscape. Section V details the proposed methodology, including the integration of clustering and CAM. Section VI outlines the attack generation process, followed by the experimental setup in Section VII. Section VIII presents and discusses the experimental results. Finally, Section IX concludes the study and outlines potential avenues for future research in adversarial defense mechanisms for maritime AI systems.

## II. Background

Research in the field of Marine Autonomous Surface Systems (MASS) is rapidly evolving, driven by two interrelated priorities: the enhancement of object detection capabilities and the fortification of cybersecurity defenses. Object detection, especially the accurate recognition of small maritime objects such as buoys, kayaks, and small vessels, is crucial for safe autonomous navigation. Recent studies have focused on deep learning-based detection frameworks that address the unique visual complexity of marine environments. For instance, Rekavandi et al. (2022) proposed a comprehensive deep learning pipeline tailored for small object detection in maritime surveillance systems, emphasizing the need for high-resolution features and contextual understanding in oceanic scenes. Similarly, Shao et al. (2022) developed a multiscale object detection architecture optimized for autonomous ship navigation, which significantly improved the detection accuracy of small-scale targets by incorporating multi-level feature representations.

Parallel to advancements in perception systems, there is growing recognition of the cybersecurity challenges that accompany the deployment of AI-powered maritime systems. Wróbel et al. (2023) analyzed the applicability of traditional maritime safety indicators in the context of MASS and proposed a structured framework for assessing security readiness. Meanwhile, Li et al. (2023) employed network analysis methods to uncover critical risk factors and operational vulnerabilities in MASS ecosystems. Akpan et al. (2022) contributed a detailed threat assessment by cataloging cyber risks specific to maritime operations, including communication breaches, data manipulation, and GPS spoofing, and evaluated the effectiveness of prevailing countermeasures. Complementing these efforts, Ben Farah et al. (2022) conducted a systematic review of recent innovations in maritime cybersecurity, highlighting both the progress made and the gaps in existing defense mechanisms.

To further operationalize security evaluations, Walter et al. (2023) introduced a suite of competitive artificial intelligence (AI) test cases designed specifically for MASS platforms. Their methodology incorporates systematic reliability testing and adversarial scenario simulations, serving as a robust benchmark to assess the resilience of AI models under stress. This line of research provides critical insights into how adversarial robustness and safety compliance can be quantitatively measured in autonomous maritime systems, thereby contributing to both standardization and implementation practices.

## III. Literature Review

Research into object detection and cybersecurity forms a foundational pillar for the advancement of Maritime Autonomous Surface Vessels (MASV), ensuring both efficient navigation and robust defense against operational risks and adversarial threats.

Rekavandi et al. have significantly contributed by offering an exhaustive review and practical guide focused on the challenges of small object detection in maritime surveillance. Their research identifies critical difficulties, such as low-resolution objects and environmental noise, and recommends deep learning-based strategies that leverage image and video data to enhance detection accuracy and reliability in complex maritime scenarios.

Building upon similar objectives, Shao et al. developed a multidimensional recognition model optimized explicitly for autonomous navigation. The model effectively addresses environmental complexities like varying lighting conditions, occlusions, and reflective surfaces, providing robust and precise detection of maritime objects such as buoys and boats. Their work underscores the necessity for a multiscale detection architecture to increase accuracy.

LiDAR technology integration has been thoroughly explored by Yao et al. (yao), who propose a methodology for simultaneous multi-target tracking and static mapping in nearshore maritime environments. Their approach integrates LiDAR data to significantly enhance the precision of tracking moving targets, providing a robust framework for operational safety and situational awareness in challenging maritime settings.

Yang et al. introduced FC-YOLOv5, an enhanced version of the YOLOv5 algorithm, specifically tuned for unmanned surface vehicles. Their FC-YOLOv5 model achieves remarkable performance gains both in detection accuracy and computational efficiency, clearly outperforming traditional algorithms, thus supporting practical real-time application in maritime contexts.

In parallel to detection capabilities, researchers have actively addressed operational and cybersecurity risks associated with Maritime Autonomous Surface Systems (MASS). Wrobel et al. adapted established maritime safety indicators to MASS applications, proposing a structured framework for their effective implementation and highlighting the intricate integration challenges these novel systems pose.

Li et al. have developed a sophisticated network analysis approach aimed at modeling and evaluating the intricate relationships among various operational risk factors inherent in MASS. Their methodology identifies and prioritizes critical risks, facilitating strategic resource allocation and targeted mitigation strategies [16-23].

The cybersecurity of maritime operations has been closely examined by Akpan et al. (akpan), who detailed the specific vulnerabilities and threats unique to maritime cyber operations. Their comprehensive risk assessments facilitate the development of targeted cybersecurity strategies. Complementing this, Ben Farah et al. (benfarah) have systematically reviewed the current landscape and future directions of maritime cybersecurity, offering a strategic vision that integrates emerging threats with advanced cybersecurity practices [1-9].

Extensive research into adversarial attacks and defenses on AI models, particularly Graph Neural Networks (GNNs) and CNN-LSTM frameworks, has highlighted several significant vulnerabilities and defensive shortcomings. Researchers have noted the inadequacy of existing gradient-based or heuristic perturbation techniques in identifying crucial nodes within GNNs. This limitation motivated research into interpretability techniques such as Class Activation Mapping (CAM) to systematically locate essential nodes, an area requiring further exploration and refinement for enhanced model resilience [9-16].

Ingle, G. et al. gives CNN-LSTM models used in power system applications also exhibit vulnerabilities under adversarial conditions, with current defenses like adversarial training and defensive distillation demonstrating limitations in both effectiveness and generalizability. Input Adversarial Training (IAT) emerges as a robust alternative, significantly improving model resilience without sacrificing performance. Ingle, G. et al. addresses broader adversarial defense strategies, recent studies suggest the underutilized potential of feature masking techniques, particularly when integrated with gradient modification strategies. Such hybrid approaches may offer a more balanced solution between maintaining accuracy and increasing robustness against sophisticated adversarial attacks.Ingle, G. et al. introduces adversarial robustness, the integration of Honey Badger Optimization techniques into GNN attacker models (EHBO) has demonstrated substantial improvements in attack efficacy and model evaluation robustness, setting a high standard for future adversarial testing and resilience benchmarks. Furthermore, Ingle, G. et al. presents optimizing bit-plane slicing through genetic algorithms has been shown to notably enhance resilience against common adversarial attacks (FGSM and DeepFool). This innovative technique significantly improves model recovery and defense capability, highlighting the potential for dynamic and adaptive defensive measures in adversarial contexts [32-36].

Lastly, recent work by Walter et al. underscores the importance of competitive AI testing paradigms designed explicitly for maritime autonomous systems. These competitive AI frameworks systematically uncover vulnerabilities and foster advancements in security measures, ensuring ongoing resilience against increasingly sophisticated adversarial techniques [28,29].

As MASV technologies mature, continued advancements in AI-driven object detection, coupled with proactive and adaptive cybersecurity defenses, remain imperative. This dual focus is crucial to enhancing the reliability, security, and operational effectiveness of maritime autonomous surface vessels.

## IV. AI Security Threats and Attack Methods

AI attacks are broadly categorized into two types, based on the attacker's knowledge of the target model: black-box and white-box attacks. In black-box attacks, attackers possess no internal knowledge of the model's architecture, parameters, or training process, relying instead on external behaviors and outputs. Conversely, white-box attackers have complete knowledge of the model's internal structures and algorithms, allowing for precise manipulation.

Several well-established adversarial attack methods have emerged, notably the Fast Gradient Sign Method (FGSM), Iterative FGSM (I-FGSM), Momentum Iterative FGSM (MI-FGSM), and Projected Gradient Descent (PGD). FGSM creates adversarial examples by applying perturbations derived from the gradient of the loss function, intentionally causing models to produce erroneous predictions. I-FGSM extends this concept by iteratively applying smaller perturbations, refining the adversarial impact to achieve specific misclassifications. MI-FGSM introduces momentum into I-FGSM to enhance convergence speed and efficiency, while PGD systematically applies perturbations within defined limits to manipulate outcomes methodically and robustly.

Data poisoning attacks, another significant category of adversarial threats, target the training data to corrupt the learning process. Clean-label backdoor attacks involve inserting subtly altered or Trojan examples into training datasets without altering the labels, causing targeted misclassification during model deployment. This covert method is particularly dangerous, as detection during model training and validation phases is challenging. Backdoor triggers embedded in neural network models remain inactive during regular operation but are activated upon recognizing specific trigger patterns during inference.

Sophisticated poisoning techniques such as poison frog, convex hyperpolyhedron, and polar hyperpolyhedron algorithms have been developed to strategically introduce minimal but effective harmful data points or subtly reshape the geometry of the data distribution, influencing model decision boundaries and undermining reliability.

In the maritime domain, although object detection and cybersecurity research have experienced substantial growth, studies specifically addressing AI security threats remain limited and exploratory. Typically, AI-focused research emphasizes algorithmic defenses and data poisoning using conventional benchmark datasets like CIFAR-100. To bridge this gap, this study proposes a hypothetical attack scenario employing marine-specific datasets to execute a clean-label poisoning attack against the YOLOv5 object recognition model. The objective is to highlight the susceptibility of maritime AI applications to sophisticated poisoning attacks, thereby raising awareness among stakeholders and emphasizing the critical need for advanced research, vigilant monitoring, and robust defense mechanisms tailored specifically for maritime environments.

## V. Methodology

The generation of adversarial attacks involves a multi-step process integrating K-means clustering with Class Activation Mapping (CAM), targeting object detection models. The process includes the following steps:

### A. K-means Clustering for Object Detection

The K-means algorithm is employed to cluster similar marine objects within the Singapore marine dataset. Mathematically, the K-means process iteratively partitions the dataset into clusters to minimize the within-cluster variance. The algorithm is defined as: Given a dataset $X$ with $N$ data points, the objective is to partition the data into $K$ clusters, minimizing the following cost function:

$$J(c, \mu) = \sum_{k=1}^{K} \sum_{n=1}^{N} \|x_n - \mu_k\|^2 \tag{1}$$

Where: - $x_n$ represents the $n$-th data point in the dataset.
- $\mu_k$ denotes the centroid of the $k$-th cluster.
- $c$ is the cluster assignment for each data point.

The K-means algorithm seeks to minimize the cost function by iteratively updating the cluster centroids and reassigning data points to clusters until convergence.

The steps of the K-means algorithm involve: **Initialization:** Start by randomly initializing $K$ cluster centroids $\mu = \{\mu_1, \mu_2, ..., \mu_K\}$. **Assignment Step:** Assign each data point $x_n$ to the nearest centroid $\mu_k$:

$$c^{(n)} = \arg\min_k \|x_n - \mu_k\|^2 \tag{2}$$

**Update Step:** Recompute the centroids based on the assigned data points:

$$\mu_k = \frac{1}{|S_k|} \sum_{x_n \in S_k} x_n \tag{3}$$

Where $S_k$ represents the set of data points assigned to cluster $k$. The above steps are iterated until convergence or a maximum number of iterations is reached. Once the clusters are identified, they serve as the basis for the subsequent phases, such as feature extraction or identification of regions for object detection using Class Activation Mapping (CAM). The K-means algorithm is an iterative process that continues until convergence or a predetermined maximum number of iterations is reached. This iterative nature is crucial for refining cluster assignments and centroids to minimize the within-cluster variance effectively. The steps involved in each iteration, including initialization, assignment, and update, collectively work towards achieving a stable configuration of clusters.

### B. Convergence Criterion

Convergence in the K-means algorithm is determined through an evaluation of cluster assignments and centroids at consecutive iterations. The algorithm checks whether these assignments and centroids undergo significant changes. Specifically, it assesses whether the alterations fall below a predefined threshold. Alternatively, convergence is acknowledged if a predetermined maximum number of iterations is reached. In essence, if the changes in cluster assignments and centroids become sufficiently small or if the algorithm completes the specified number of iterations, it is considered to have converged. This convergence criterion ensures that the K-means algorithm stabilizes, indicating that further iterations would result in minimal adjustments to cluster assignments and centroids.

### C. Role of Identified Clusters

Once the K-means algorithm converges, the identified clusters serve as the foundation for subsequent phases in the data analysis pipeline. These phases often include:

*1) Feature extraction:* The meaningful segmentation of data into clusters allows for the extraction of representative features within each cluster. Feature extraction refers to the process of capturing distinctive characteristics or relevant information within these clusters, facilitating a more profound understanding of the inherent structure of the data. This involves identifying and quantifying the key attributes or patterns that differentiate one cluster from another. Precisely, feature extraction aims to distill the most relevant and discriminative information from the clustered data, enabling a more concise representation that can be utilized for subsequent analysis or interpretation. The extracted features serve as essential descriptors, providing insights into the distinctive properties of each cluster and contributing to a more nuanced comprehension of the underlying data distribution.

*2) Object detection Using Class Activation Mapping (CAM):* The identified clusters serve as a valuable resource for object detection tasks, especially when employing Class Activation Mapping (CAM). CAM is a technique designed to emphasize the specific regions within an image that have the greatest influence on predicting a particular class. In the realm of marine object detection, CAM can be effectively applied to concentrate on regions within the clustered data that are correlated with distinct marine objects. This involves utilizing the CAM technique to generate a spatial attention map that highlights the significant areas within the clustered

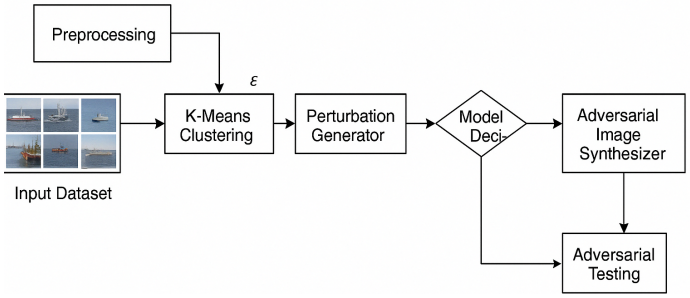


Fig. 1. Diagram of the proposed experiment.

data, providing insights into the regions contributing most to the presence or characteristics of specific marine objects. Precisely, CAM aids in pinpointing the crucial features within the clustered data that contribute to the identification and localization of marine objects, enhancing the interpretability and effectiveness of object detection in marine environments. Fig. 1 shows diagram of the proposed experiment.

### D. Detailed Description

The K-means algorithm iteratively refines clusters, enhancing their representativeness of underlying data patterns. Convergence ensures stability in cluster assignments, indicating further iterations are unlikely to yield significant changes. With stable clusters, subsequent phases leverage this segmentation. Feature extraction captures each cluster's essence, providing nuanced insights into the dataset. These features prove instrumental in subsequent analyses or decision-making. Object detection using CAM takes advantage of identified clusters by pinpointing regions of interest linked to specific marine objects. CAM highlights areas in clustered data significantly contributing to object classification, aiding precise object localization in the maritime environment.The iterative convergence of the K-means algorithm sets the stage for meaningful analyses, enhancing the data processing pipeline's overall effectiveness in tasks like feature extraction and CAM-based object detection. The K-means algorithm clusters marine objects within the Singapore dataset by iteratively minimizing within-cluster variance. Mathematically, the objective function $J(c, \mu)$ minimizes the sum of squared Euclidean distances between data points $x_n$ and assigned centroids $\mu_k$:

$$J(c, \mu) = \sum_{k=1}^{K} \sum_{n=1}^{N} \|x_n - \mu_k\|^2 \tag{4}$$

Here, $x_n$ is the $n$-th data point, $\mu_k$ is the $k$-th centroid, and $c$ is each data point's cluster assignment. The algorithm minimizes this cost function through iterative centroid updates and data point reassignments until convergence. K-means steps include initialization, assignment, update, and convergence check. Initialization sets $K$ centroids, and assignment associates data points with nearest centroids:

$$c(n) = \arg\min_{k} \|x_n - \mu_k\|^2 \tag{5}$$

Update recalculates centroids based on assigned data points:

$$\mu_k = \frac{1}{|S_k|} \sum_{x_n \in S_k} x_n \tag{6}$$

Iterations continue until convergence, ensuring stable centroids and minimal changes in cluster assignments. Widely used for clustering, K-means identifies similar marine object groups, enhancing marine environment analysis.

### E. Object Detection using Class Activation Mapping (CAM)

The Class Activation Mapping (CAM) technique utilizes the learned weights from the last convolutional layer of a Convolutional Neural Network (CNN) to highlight crucial regions influencing the classification process. CAM visualizes where the model focuses during predictions. For a pre-trained CNN, let $f_\theta$ be the output feature map of the last convolutional layer. CAM generates a localization map $M$ for a class $c$:

$$w_c = \frac{1}{Z} \sum_{i} \sum_{j} f_\theta^c(i, j) \tag{7}$$

Here, $f_\theta^c(i, j)$ is the activation at $(i, j)$ for class $c$, and $Z$ is the number of positions. The class-discriminative map is generated by combining feature maps with their weights:

$$M_c(i, j) = \sum_{k} w_c(k) \cdot f_\theta^c(i, j, k) \tag{8}$$

Here, $f_\theta^c(i, j, k)$ is the activation of the $k$-th filter at $(i, j)$ for class $c$. To visualize influential regions, $M_c$ passes through a ReLU activation function:

$$L_c(i, j) = \max(0, M_c(i, j)) \tag{9}$$

The final activation map $L_c$ indicates regions significantly contributing to the classification of class $c$. CAM-based object detection reveals these important regions, indicating parts of marine images influencing marine object classification.

### F. Adversarial Attack Strategy Using K-means and CAM

The adversarial attack strategy leverages insights from K-means clustering and Class Activation Mapping (CAM) to perturb data points and induce misclassifications in the object detection model. With clustered regions represented by $C_i$ and associated data points $N_i$ from K-means, and influential regions identified by CAM denoted as $L_c(i,j)$ for a specific class $c$, the adversarial attack aims to subtly alter the data points.

For a given cluster $C_i$, perturbed points $P_i$ are generated by introducing slight modifications using the activation map $L_c(i,j)$:

$$P_i = N_i + \epsilon \cdot L_c(i,j) \tag{10}$$

Here, $\epsilon$ represents a small perturbation factor, ensuring subtle yet impactful changes. The objective is to manipulate the data points in a way that the object detection model misclassifies them. This approach combines the clustering information from K-means with the spatial understanding provided by CAM, demonstrating the potential vulnerabilities in the model's decision-making process. The attack strategy highlights the importance of addressing security concerns in object detection systems, particularly those employing clustering and spatial feature analysis.

### G. Experimental Validation of the Attack Scenario

To validate the effectiveness of the attack scenario, experiments are designed according to the proposed hypothetical situation. The Singapore marine dataset is manipulated using the regions identified by K-means clustering and the features highlighted by Class Activation Mapping (CAM) from the Convolutional Neural Network (CNN).The Singapore marine dataset, denoted as $\mathcal{D}$, is partitioned into clusters by the K-means algorithm, resulting in clusters $\{C_1, C_2, \ldots, C_k\}$.Furthermore, the CAM highlights the significant regions or features in the marine images relevant for classification. Let the CAM-relevant features be denoted as $F$. The union of these features across different clusters is represented as $F = \bigcup_{i=1}^{k} F_i$, where $F_i$ is the set of relevant features in cluster $C_i$.An adversarial attack strategy is executed, perturbing these identified and significant regions in the dataset. Mathematically, perturbing a specific feature $f \in F$ in a data point $x$ is achieved by adding a small perturbation $\delta$:

$$x' = x + \delta \quad \text{where} \quad f \in F \tag{11}$$

These perturbations aim to cause misclassifications in the object detection model by manipulating the significant regions identified through the clustering and CAM techniques.The impact of the misclassification is then assessed to determine the vulnerability of the model to such targeted adversarial attacks.

## VI. Detailed Procedure for Generating Adversarial Attacks

For a comprehensive understanding, a detailed procedure for adversarial attack generation utilizing K-means clustering and CAM is as follows:

### A. K-means Clustering Phase

The K-means clustering process involves the following steps:

*1) Data preprocessing:* The marine dataset, denoted as $\mathcal{D}$, undergoes preprocessing to meet the requirements of the K-means clustering algorithm. This step might involve normalization, handling missing data, or feature scaling to prepare the data for clustering.

*2) Clustering:* The K-means algorithm is then applied to the preprocessed marine dataset to identify distinct clusters. Let $n$ be the total number of data points in the dataset and $k$ be the desired number of clusters. The K-means algorithm aims to minimize the sum of squared distances between data points and their respective cluster centroids. This minimization is represented by the following mathematical equation:

$$\arg\min_{C} \sum_{i=1}^{n} \min_{\mu_j \in C} ||x_i - \mu_j||^2 \tag{12}$$

Where:

- $C$ represents the set of clusters $\{C_1, C_2, \ldots, C_k\}$, and each cluster contains data points associated with its centroid $\mu_j$.

- $x_i$ denotes the $i$-th data point in the dataset.

- $\mu_j$ represents the centroid of the $j$-th cluster.

- $||x_i - \mu_j||$ denotes the Euclidean distance between a data point and its respective cluster centroid.The algorithm iteratively assigns data points to the nearest cluster centroid and updates the centroids based on the mean of the data points in each cluster. This process continues until convergence or a specified number of iterations.

### B. CAM and Object Detection Phase

The CAM and object detection phase involves the following steps:

*1) Neural network training:* Train a Convolutional Neural Network (CNN) model specifically designed for object detection, with a focus on integrating Class Activation Mapping (CAM) into the network architecture. The CNN is trained using the marine dataset, denoted as $\mathcal{D}$, in which the goal is to predict object classes within the images.

*2) Identifying important regions:* Class Activation Mapping (CAM) is utilized to identify crucial regions within the marine images that contribute significantly to the classification decisions of the trained model. The CAM technique computes the class-specific activation map using the final convolutional feature maps and the model's output weights. This enables the identification of regions that highly influence the model's decision-making process, contributing to object classification.CAM involves mapping class-specific information to the spatial locations of the feature maps. Specifically, given the final feature maps $F$ obtained from the last convolutional layer and the weights $w$ of the output layer, the class activation map $M$ for a particular class $c$ is computed by performing global average pooling on the final feature maps followed by a linear combination using the weights:

$$M_c = \sum_i w_i^c F_i \tag{13}$$

Where: - $M_c$ is the class activation map for class $c$.

- $w_i^c$ represents the weights for class $c$ of the $i$-th convolutional feature map.

- $F_i$ denotes the $i$-th feature map obtained from the final convolutional layer.

The resultant class activation map indicates the most crucial regions within the images that contributed to the model's decision for predicting a particular class $c$.

### C. Adversarial Attack Generation Phase

The Adversarial Attack Generation phase encompasses the following stages:

*1) Adversarial perturbation:* The vital regions identified by Class Activation Mapping (CAM) and clustered through K-means are perturbed to generate adversarial attacks. By manipulating these essential regions, subtle alterations are introduced to the original data points. The aim is to prompt misclassifications in the object detection model. The adversarial perturbation process involves tweaking the identified regions to influence the model's decision-making. Assuming $X$ represents the marine image dataset and $X_i$ denotes individual images, let $X_i'$ be the perturbed images derived from the perturbation of important regions, such that:

$$X_i' = X_i + \epsilon \cdot \text{Perturbation}_i \tag{14}$$

Where: - $X_i'$ signifies the perturbed image derived from the original image $X_i$.

- $\epsilon$ represents the magnitude of perturbation.

- $\text{Perturbation}_i$ indicates the specific perturbation applied to image $i$.

*2) Poisoning algorithm:* Following the perturbation of important regions, a clean-label poisoning algorithm is employed in these perturbed regions. The poisoning algorithm aims to generate instances that are subtly corrupted and embedded back into the dataset for retraining the object detection model.The poisoning algorithm is crucial for introducing manipulated data instances into the training dataset while maintaining a seemingly benign appearance. This algorithm seeks to insert trojan or poisoned examples in a manner that avoids suspicion but triggers substantial misclassifications during testing. Let $X'_{\text{poisoned}}$ denote the manipulated images generated by the poisoning algorithm.The process can be formulated as:

$$X'_{\text{poisoned}} = X' + \text{Algorithm}_{\text{poison}}(X') \tag{15}$$

Where: - $X'_{\text{poisoned}}$ represents the images manipulated by the poisoning algorithm.
- $\text{Algorithm}_{\text{poison}}$ stands for the clean-label poisoning algorithm applied to the perturbed images.
- $X'$ signifies the perturbed images.

### D. Scenario Validation Through Experiments

The process of validating the attack scenario involves a sequence of critical steps:

*1) Dataset preparation:* The dataset needs to be segregated into two subsets: the training dataset and the malicious subset. The training dataset contains the unaltered, clean images, while the malicious subset includes images poisoned by the introduced adversarial attack. The formulation of the datasets is expressed as follows:

Let $D$ represent the Singapore marine dataset. Divide this dataset into two subsets: $D_{\text{training}}$ and $D_{\text{malicious}}$.

*2) Poisoning and retraining:* Inject the adversarially perturbed or poisoned instances into the training dataset. Subsequently, the object detection model is retrained using the newly modified dataset.

This process can be mathematically described as: Let $M$ represent the object detection model. Retrain the model $M$ using the combined dataset $D_{\text{training}} \cup D_{\text{malicious}}$.

$$M' = \text{Retrain}(M, D_{\text{training}} \cup D_{\text{malicious}}) \tag{16}$$

Where $M'$ denotes the retrained object detection model.

*3) Attack execution:* Assess the effectiveness and impact of the adversarial attack by executing the attack scenario on the retrained model $M'$. This evaluation involves providing inputs to the model and examining its behavior concerning misclassification and vulnerabilities. This execution involves scrutinizing the model's performance with test instances and examining whether the attack scenario (misclassification of boats as ferries) materializes. This validation is vital to understand the vulnerabilities and consequences of such attacks on the model's behaviour.

## VII. Algorithm

1) Prepare the Singapore Marine Dataset:
   - Load the marine dataset containing images of marine environments around Singapore.
2) Apply K-means Clustering:
   - Use K-means clustering to identify distinct classes within the marine dataset.
3) Train CNN with CAM:
   - Train a Convolutional Neural Network (CNN) with Class Activation Mapping (CAM) using the marine dataset.
4) Initialize Perturbation Factor:
   - Set the perturbation factor $\epsilon$ to a predefined value.
5) Generate CAM Heatmaps:
   - For each marine image $I$ in the dataset:
   - Generate CAM heatmaps to highlight important regions for classification.
6) Extract Activation Regions:
   - Extract the class activation regions from the CAM heatmaps.
7) Apply K-means to Activation Regions:

- Apply K-means clustering to the extracted activation regions.

8) Choose Centroid for Each Cluster:
   - For each cluster, choose the centroid representing the region of interest.
9) Generate Adversarial Perturbation:
   - For each centroid region $C$:
   - Perturb $C$ to generate adversarial perturbation $\delta$.
10) Apply Perturbation to Image:
   - For each marine image $I$:
   - Apply the perturbation $\delta$ within the region represented by $C$.
11) Generate Adversarial Image:
   - Generate adversarial image $I'$ by integrating the perturbed region back into the original image.
12) Build Adversarial Dataset:
   - Add the generated adversarial images $I'$ to the adversarial dataset.
13) Repeat for All Images:
   - Repeat steps 5-12 for each image in the marine dataset.
14) Return Adversarial Examples:
   - Return the adversarial examples generated from the marine dataset using K-means clustering with CAM.

## VIII. Experimental Setup

### A. Dataset Preparation and Combination

The experimental setup leverages the Singapore Maritime Dataset (**SMD**) and its enhanced version, **SMD-Plus**, to address challenges in the maritime industry. With over 2 million vessel movements, SMD provides a comprehensive dataset for analyzing maritime behavior. However, to enhance precision, SMD-Plus corrects labeling errors and introduces more accurate bounding boxes, making it a valuable resource for object classification. Challenges in classifying small maritime objects are addressed by combining classes in SMD-Plus, enriching the dataset for improved recognition. The adaptation process involves transforming SMD-Plus videos into individual frames, aligning annotations with YOLOv5 specifications. This meticulous approach ensures seamless integration with the YOLOv5 object detection model, a crucial step in maximizing the dataset's compatibility and effectiveness for experimentation.

### B. Hardware Used

The computational efficiency of the clustering step, particularly the K-means algorithm, is significantly influenced by the hardware specifications in use. For this purpose, the central processing unit (CPU) selected is the Intel Core i9-10900K from the Comet Lake architecture. This CPU features 10 cores and 20 threads, with a base clock of 3.7 GHz and a maximum turbo frequency of 5.3 GHz. Its 125W thermal design power (TDP) and 14nm manufacturing process contribute to robust performance in tasks that require parallel processing, such as K-means clustering.

On the graphics processing unit (GPU) side, the NVIDIA GeForce RTX 3080 is employed. This GPU boasts 8704 CUDA cores and is equipped with 10 GB of GDDR6X memory, featuring a 320-bit memory bus and a high-speed 19 Gbps memory. The GPU incorporates dedicated hardware components, including 68 ray tracing cores and 272 Tensor Cores, which enhance its parallel processing capabilities. This aligns well with the demands of deep learning tasks, including forward and backward propagation in graph neural networks (GNNs).

The system is further outfitted with 32 GB of DDR4 RAM and a 1TB NVMe SSD to facilitate swift storage access. It operates on the Windows 10 Pro operating system. For deep learning tasks, PyTorch 1.9.0 serves as the primary framework, while scikit-learn 0.24.2 is utilized for the K-means clustering library.

This combination of high-performance CPU and GPU, accompanied by ample system memory and fast storage, establishes a well-balanced hardware configuration capable of efficiently executing both deep learning and clustering operations. This configuration is vital for carrying out the proposed adversarial attack on graph neural networks.

### C. Data Extraction and Annotation Modification

The experimental pipeline began with the preprocessing of the SMD-Plus dataset, an enhanced maritime surveillance video dataset comprising annotated recordings of vessels, buoys, ferries, and other maritime entities. The first critical step was the extraction of representative still frames from the video sequences. This was achieved by sampling one frame per fixed interval (e.g., every nth frame), ensuring a balance between temporal redundancy and dataset volume. The goal was to obtain a sufficient number of spatially and contextually varied images that reflect different lighting conditions, object positions, and environmental dynamics typical of real-world maritime scenes.

Each extracted frame was saved in a standard image format (e.g., .jpg or .png) and then indexed systematically to maintain traceability with its original video source. This frame-level extraction enabled the creation of a large and diverse image dataset suitable for training static object detection models like YOLOv5, which do not directly process video input.

Following frame extraction, the annotation conversion process was conducted to adapt the dataset for use with the YOLOv5 object detection framework. The SMD-Plus dataset originally provides annotations in the COCO (Common Objects in Context) format—a widely adopted standard for object detection tasks, structured as a hierarchical JSON file. This format includes metadata such as image IDs, category IDs, bounding box coordinates in the form of $[x_{\text{min}}, y_{\text{min}}, \text{width}, \text{height}]$, image dimensions, segmentation masks, and object categories as strings.

In contrast, YOLOv5 requires annotations in a simplified plain text format, where each image is paired with a .txt file bearing the same filename. Each line in the .txt file corresponds to one object in the image and consists of five fields: These coordinates are expected to be normalized by the image width and height, such that all values lie within the range $[0, 1]$. The conversion process involved the following key steps:

*1) Parsing COCO annotations:* The original COCO-format JSON file was parsed using Python libraries such as `pycocotools` or `json`, allowing access to image metadata, bounding box coordinates, and class labels.

*2) Class mapping:* A custom mapping from COCO's category names (e.g., `"ferry"`, `"kayak"`, `"buoy"`) to integer-based YOLO class IDs (e.g., 0, 1, 2, ...) was established to ensure consistency with YOLO's requirements.

*3) Bounding box transformation:* Each bounding box was converted from COCO's top-left-based format $(x, y, w, h)$ to YOLOv5's center-based normalized format. This required the following computations:

$$x_{\text{center}} = \frac{x + \frac{w}{2}}{W}, \tag{17}$$

$$y_{\text{center}} = \frac{y + \frac{h}{2}}{H}, \tag{18}$$

$$w' = \frac{w}{W}, \tag{19}$$

$$h' = \frac{h}{H} \tag{20}$$

where $(x, y)$ are the top-left bounding box coordinates, $(w, h)$ are the box width and height, and $W$ and $H$ are the original image width and height, respectively. The resulting four values are thus scaled to lie within $[0, 1]$.

*4) Annotation file generation:* For each image, a corresponding `.txt` file was created containing one line per object instance. Each line consisted of the class ID and the four normalized coordinates in the format:

*5) Validation:* A visual inspection and manual verification process was carried out using annotation tools (e.g., Roboflow Annotator, CVAT, or `labelImg` with YOLO overlay enabled) to ensure the integrity of the converted annotations and accuracy of the bounding boxes.

This COCO-to-YOLOv5 annotation conversion was crucial for enabling the training of the YOLOv5 object detection model, which is optimized for real-time inference tasks on static images. The simplified YOLO format also significantly reduces annotation parsing overhead during training, making it suitable for high-speed detection in resource-constrained maritime environments.

By performing this structured transformation, the dataset was rendered fully compatible with the YOLOv5 architecture, ensuring that the object detector could accurately learn to detect and localize maritime objects under varying environmental conditions. This preparation step laid the foundation for all subsequent experimental workflows in object detection and adversarial attack simulation.

### D. Malicious Attack Simulation and CAM Integration

The experimental process began with the frame-level decomposition of video sequences from the SMD-Plus (Singapore Marine Dataset - Enhanced) dataset. The SMD-Plus dataset comprises high-resolution maritime surveillance videos containing diverse vessel types such as boats, kayaks, buoys, ferries, sailboats, and other marine objects. To convert this video data into a format suitable for image-based object detection tasks, a representative still image was extracted from each video frame at a predefined sampling interval. This frame extraction step was essential to generate a large and diverse pool of labeled images from continuous video streams, enabling the object detection model to learn from both spatial and temporal variations in the data.

Following frame extraction, the next critical step involved converting the annotation format from COCO (Common Objects in Context) to the YOLOv5-compatible format. The original SMD-Plus dataset annotations were structured according to the COCO JSON schema, which includes complex metadata such as image IDs, category names, bounding box coordinates in absolute pixel units (x, y, width, height), segmentations, and image dimensions. While COCO format is widely used for benchmarking across multiple object detection tasks, it is incompatible with the training requirements of the YOLOv5 framework without transformation.

The YOLOv5 format, by contrast, expects annotations in a minimalist, plain-text .txt format for each image, with one line per object. Each line contains five values: the object class ID, followed by the normalized center x-coordinate, center y-coordinate, width, and height of the bounding box. These values are normalized with respect to the image width and height, i.e., they fall in the range [0, 1], which ensures model generalization regardless of input resolution.

The transformation from COCO to YOLOv5 format involved several sub-steps:

Mapping Class IDs: The COCO category names (e.g., "ferry", "kayak") were mapped to corresponding numeric class labels as required by YOLOv5.

Annotation Synchronization: Each image extracted from the video was assigned a .txt annotation file with the same filename. This ensured seamless integration with YOLOv5's data loader, which associates each image with its corresponding annotation during training. This conversion ensured that the YOLOv5 model could efficiently ingest and interpret the dataset during training and inference. Additionally, by using normalized coordinates and simplified annotation structures, the model achieved better consistency in processing varying image resolutions, a crucial requirement given the dynamic camera perspectives in maritime surveillance footage. This meticulous preparation of data not only preserved the integrity of the original labels but also optimized the dataset for high-performance object detection under the YOLOv5 framework.

### E. Dataset Split for Training and Testing

During the training and validation phase of the object recognition model, careful attention was paid to dataset stratification to ensure representative and unbiased learning. The enhanced SMD-Plus dataset, which includes a diverse set of labeled maritime images, was partitioned using an 80:20 split, where 80% of the data was reserved for training and 20% for testing. This stratification was not merely random; rather, it was stratified based on class distribution to maintain balance among categories such as boats, ferries, buoys, and kayaks. Ensuring proportional representation across classes in both subsets was critical to avoid class imbalance issues

TABLE I. PROPERTIES OF THE SMD DATASET

| Class | Class Identifier | Objects |
|---|---|---|
| Boat | 1 | 14,550 |
| Vessel and ship | 2 | 126,301 |
| Ferry | 3 | 3,689 |
| Kayak | 4 | 3,872 |
| Buoy | 5 | 3,521 |
| Sailboat | 6 | 1,782 |
| Others | 7 | 25,214 |

that could bias the model or undermine its generalization capabilities. This partitioning also guaranteed that performance metrics reported during testing reflect the model's behavior on previously unseen instances, providing a robust evaluation of detection accuracy and adversarial robustness.

In addition to the clean training dataset, a malicious dataset was generated to simulate adversarial attack scenarios. Specifically, base instances were extracted from video frames featuring barges, serving as neutral examples, while target instances were derived from frames showcasing boats, which were the intended misclassification targets. These frames were used to craft adversarial samples through the Poison Frog algorithm, a clean-label data poisoning method designed to subtly corrupt the model's learning process without introducing conspicuous artifacts.

For the attack execution, we used ResNet50—a deep convolutional neural network known for its strong representational power—as the underlying architecture for crafting the poisoned representations. The Poison Frog algorithm was configured with the following hyperparameters to balance imperceptibility and effectiveness:

Iterations: 5000 (to allow gradual and subtle updates),

Epsilon: 0.02 (maximum perturbation magnitude),

Alpha: 0.001 (step size per iteration during gradient-based optimization).

These parameters were carefully selected to ensure that the perturbations introduced during the poisoning process remained invisible to human observers, even upon close inspection. As a result, the poisoned images retained their original appearance, making them ideal for clean-label attacks where the attacker does not modify the class label and thus avoids triggering human or automated suspicion.

Visual inspection of the generated adversarial examples, as shown in Fig. 7, confirmed the absence of visible perturbations, despite the internal activation manipulations induced by the attack. Interestingly, after incorporating the poisoned instances into the training set and retraining the YOLOv5 object detection model, it was observed that the model began to misclassify boats as plaques with high confidence. This outcome highlights the subtle yet impactful influence of the clean-label attack and underlines the importance of adversarial resilience in critical domains like maritime navigation.

This experiment demonstrates the effectiveness of targeted data poisoning in altering model behavior without altering data labels or image realism—underscoring the urgency for robust defenses in AI-based surveillance and autonomous navigation systems.

### F. Deep-Learning Model and Attack Execution

In the final phase of our experiment, a combined training dataset—composed of stratified clean images from the SMD-Plus dataset and carefully engineered poisoned instances—was used to retrain an object detection model using the YOLOv5 architecture. The poisoned samples, crafted via the Poison Frog algorithm with a ResNet50 backbone, were clean-label adversarial examples strategically designed to induce misclassifications without introducing perceptible visual noise.

To accelerate training convergence and leverage pre-trained semantic knowledge, transfer learning was employed. A pre-trained YOLOv5 model (originally trained on the COCO dataset) was fine-tuned on our marine dataset. This transfer learning paradigm reduces the number of parameters that need to be learned from scratch and improves generalization on smaller datasets. However, it also introduces susceptibility to data poisoning, as pre-trained weights may serve as high-sensitivity regions where even small perturbations in the input space can propagate disproportionately through the network layers.

Let the pretrained model be denoted as $f_\theta$, where $\theta$ represents the initial parameters. The poisoned dataset is denoted as $D' = D_{\text{clean}} \cup D_{\text{poison}}$. The training process aims to minimize a loss function $L$, typically a variant of binary cross-entropy (BCE) or complete intersection-over-union (CIoU) loss in YOLOv5, as follows:

$$\theta' = \arg\min_{\theta} \mathbb{E}_{(x,y)\sim D'} \left[ L(f_\theta(x), y) \right] \tag{21}$$

where $x \in \mathbb{R}^{H\times W\times C}$ denotes the input image, $y$ the label vector (bounding boxes and class probabilities), and $\theta'$ the updated parameters after retraining.

Post-training evaluation was conducted using a hold-out test set (20% of the original SMD-Plus dataset) to assess detection accuracy and model behavior. Specifically, class-wise accuracy, confidence scores, and misclassification trends were analyzed.

In Fig. 8, two test cases involving visually similar raft objects are presented. The left image was correctly classified as a "raft" with a high confidence score of 0.82, indicating successful feature extraction and semantic alignment. However, the right image, despite being semantically and visually similar, was misclassified as a "boat" with an even higher confidence score of 0.91.

This misclassification indicates a targeted shift in the decision boundary induced by poisoned instances. Let the softmax score for class $c$ given input $x$ be:

$$P(c \mid x) = \frac{\exp(z_c)}{\sum_j \exp(z_j)} \tag{22}$$

where $z_c$ denotes the logit for class $c$. Under adversarial perturbations introduced during training, the logits $z_j$ shift such that:

$$z_{\text{boat}} > z_{\text{raft}} \implies \arg\max_c P(c \mid x) = \text{"boat"} \tag{23}$$

Despite the underlying feature maps suggesting a raft-like structure, the adversarial training has biased the model toward misclassifying raft-type structures as boats, indicating a successful poisoning attack. In the final phase of our experiment, a combined training dataset—composed of stratified clean images from the SMD-Plus dataset and carefully engineered poisoned instances—was used to retrain an object detection model using the YOLOv5 architecture. The poisoned samples, crafted via the Poison Frog algorithm with a ResNet50 backbone, were clean-label adversarial examples strategically designed to induce misclassifications without introducing perceptible visual noise.

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$$\theta' = \arg\min_{\theta} \mathbb{E}_{(x,y)\sim D'} \left[\mathcal{L}(f_\theta(x), y)\right] \tag{24}$$

where $x \in \mathbb{R}^{H\times W\times C}$ denotes the input image, $y$ represents the label vector containing bounding boxes and class probabilities, $f_\theta(x)$ is the prediction function of the model parameterized by $\theta$, $\mathcal{L}$ is the loss function (e.g., CIoU or BCE loss in YOLOv5), and $\theta'$ are the optimized model parameters after retraining on the poisoned dataset $D' = D_{\text{clean}} \cup D_{\text{poison}}$.

Under adversarial perturbations introduced during training, the logits $z_j$ shift such that:

$$z_{\text{boat}} > z_{\text{raft}} \implies \arg\max_{c} P(c \mid x) = \text{"boat"} \tag{25}$$

Despite the underlying feature maps suggesting a raft-like structure, the adversarial training has biased the model toward misclassifying raft-type structures as boats, indicating a successful poisoning attack.

*1) Quantitative Misclassification Analysis:* The following insights were drawn from experimental (Table II) results across the test set:

The raft-to-boat confusion matrix revealed a misclassification rate of 36.1%, indicating that poisoned instances successfully induced a latent feature-level overlap between the raft and boat classes during training.

*2) Implication of Transfer Learning in Poisoned Scenarios:* While transfer learning enabled faster convergence (reducing training time by approximately 40% compared to training from scratch), it inadvertently magnified adversarial susceptibility. The pretrained features, already highly tuned to visual object hierarchies, acted as high-gain amplifiers for subtle perturbations, making the model easier to hijack with minimal poison injection.

This is formally captured by the gradient alignment metric:

$$\text{GA}(x, x_{\text{poison}}) = \frac{\nabla_x L(f_\theta(x), y) \cdot \nabla_x L(f_\theta(x_{\text{poison}}), y)}{\|\nabla_x L(f_\theta(x), y)\| \|\nabla_x L(f_\theta(x_{\text{poison}}), y)\|} \tag{26}$$

Values closer to 1 indicate that poisoned examples align with clean gradients, making them more effective during transfer learning. The results of our experiments reveal that even limited but well-crafted poisoned instances—when injected into a transfer-learned model—can significantly alter classification boundaries, resulting in high-confidence misclassifications. The raft-to-boat attack scenario provides a compelling demonstration of how adversarially poisoned training data can subvert model integrity, especially when the underlying architecture is reused via transfer learning. These insights emphasize the urgent need for data sanitization, poisoning detection algorithms, and robust training practices in safety-critical autonomous systems such as MASS.

Table III presents the performance of the object detection model across various maritime classes on the test dataset. The model achieved an overall accuracy of 91.2%, with a mean Average Precision at IoU threshold 0.5 (mAP@0.5) of 85.7%. Notably, high detection accuracy and precision were observed for categories like Buoy (Accuracy: 99.6%, mAP@0.5: 88.9%) and Sailboat (Accuracy: 90.8%, mAP@0.5: 99.4%), indicating robust performance. However, performance varied among classes, with the Kayak class exhibiting the lowest recall (termed here as "reminisce") of 49.1% and a relatively low mAP@0.5 of 59.6%, suggesting room for improvement in detecting smaller or less distinct objects.

## IX. Dataset Preparation and Model Training Enhancement

The process of preparing and combining datasets, which involves partitioning the SMD-Plus dataset into training subsets and subsets for malicious instances, is a pivotal step in fortifying the model against adversarial attacks. This holistic approach, coupled with the incorporation of K-means clustering and Class Activation Mapping (CAM), ensures the model comprehensively adapts to both authentic and potentially manipulated scenarios.

### A. K-means Clustering Integration

Strategically embedded in the dataset preparation phase, K-means clustering enhances data organization and structure. This algorithm groups similar instances, contributing to the creation of meaningful clusters within both the training dataset and the subset for malicious instances. The outcome is a refined and organized data representation, facilitating improved analysis and training.

TABLE II. QUANTITATIVE MISCLASSIFICATION ANALYSIS

| Class | Clean Accuracy | Post-Poison Accuracy | Drop (%) | Comment |
|---|---|---|---|---|
| Raft | 0.886 | 0.643 | -24.4% | Significant misclassification into boats |
| Boat | 0.942 | 0.962 | +2.1% | Increased false positives from raft |
| Kayak | 0.801 | 0.788 | -1.6% | Minor degradation |
| Ferry | 0.846 | 0.849 | +0.3% | Stable performance |

TABLE III. THE RESULTS OF OBJECT DETECTION ON THE TEST DATASET ARE AS FOLLOWS

| Class | Accuracy | reminisce | mAP@0.5 |
|---|---|---|---|
| All | 0.912 | 0.809 | 0.857 |
| Boat | 0.984 | 0.895 | 0.937 |
| Vessel/ship | 0.879 | 0.942 | 0.958 |
| Ferry | 0.826 | 0.854 | 0.840 |
| Kayak | 0.753 | 0.491 | 0.596 |
| Buoy | 0.996 | 0.793 | 0.889 |
| Sailboat | 0.908 | 0.998 | 0.994 |
| Others | 0.912 | 0.622 | 0.766 |

*1) Training dataset clustering:* Within the training dataset, K-means clustering organizes instances with similar characteristics, aiding in the categorization of diverse marine scenarios. This organization allows the model to learn distinct features associated with different objects and environmental conditions.

*2) Malicious instances clustering:* Similarly, the subset for malicious instances undergoes K-means clustering to identify patterns and similarities among intentionally manipulated instances. Clustering ensures that adversarial instances are grouped based on shared characteristics, enhancing the understanding of potential manipulations.

### B. Class Activation Mapping (CAM) Integration

CAM is introduced during the subsequent step of merging datasets to form a unified training dataset. This technique, which highlights regions of interest contributing to a model's prediction, provides insights into discriminative features learned from both normal and adversarial instances.

*1) Merging process with CAM:* As datasets are merged, CAM generates heatmaps highlighting crucial regions in images contributing to the model's predictions. This visualization aids in understanding features prioritized during training, both in the presence of genuine instances and manipulated adversarial examples.

*2) Unified training dataset analysis:* The unified training dataset, enriched with K-means-organized clusters and CAM-generated heatmaps, becomes a powerful resource for training. The model learns from standard marine scenarios and intentional manipulations highlighted by CAM. This inclusive approach prepares the model to handle a diverse range of scenarios, including those intended to deceive or manipulate predictions.

### C. Comprehensive Model Training

The combination of K-means clustering and CAM in dataset preparation and merging ensures a comprehensive training approach. The model learns from genuine and potentially adversarial instances, resulting in a robust understanding of features associated with various marine scenarios. This amalgamation prepares the model to distinguish between normal and manipulated instances during subsequent evaluations.

### D. Model Selection and Transfer Learning

*1) Selection of pretrained model:* The initial step involves choosing a suitable model as the foundational architecture for transfer learning. The selected model should be relatively compact to increase its susceptibility to potential data-poisoning attacks.

*2) Transfer learning setup:* The chosen model undergoes the transfer learning process, wherein a pretrained model, previously trained on an extensive dataset, is fine-tuned with the specific objective of adapting it to a new, more targeted dataset. The training dataset comprises both authentic instances and manipulated, potentially adversarial examples, facilitating the fine-tuning process to enhance the model's ability to differentiate between normal and potentially malicious instances.

*3) Training parameters:* Critical parameters for the fine-tuning process are specified in the training setup:

*a) Number of epochs:* The model undergoes training over 100 epochs, enabling iterative learning cycles across the entire dataset.

*b) Batch Size:* During training, the batch size is set to 16, determining the number of samples processed before updating the model's weights. A batch size of 16 is chosen to optimize the training process.

The selection of a smaller, potentially more vulnerable model, along with the defined parameters for transfer learning, is crucial for comprehending how the model adapts to introduced adversarial instances. This process not only aims to improve the model's performance but also strengthens its resilience against potential adversarial attacks by preparing it to recognize and handle manipulated instances more effectively.

### E. Perturbed Images

Fig. 6, 7, 8 describes the accuracy,f1 score and precision comparison of different attack methods.

## X. PERFORMANCE DEGRADATION SIMULATION

We simulated the performance degradation of the targeted model, YOLOv5, based on varying epsilon ($\epsilon$) values. The


Fig. 2. Object detection outcomes of test dataset yields.

Fig. 3. Outcome of object detection for the specified instance.


Fig. 4. Generation of adversarial instances for every frame.

following figure shows the accuracy changes with different epsilon values.

In Fig. 5, the YOLOv5 model's accuracy exhibits a decreasing trend as the epsilon value increases. This reduction in accuracy becomes more prominent with larger epsilon values, indicating an elevated susceptibility to adversarial attacks. Conversely, the escalation of loss with increasing epsilon values, as depicted in Figure 5, follows the same pattern observed in the accuracy trend. Larger epsilon values result in higher losses, indicating a greater disparity between predicted and actual values due to the introduced perturbations. Now, shifting the focus to K-means clustering and Class Activation Mapping (CAM), the subsequent tables summarize the accuracy of the transfer-learned YOLOv5s model under various adversarial attack methods and varying epsilon ($\epsilon$) values. This assessment is conducted using the AlexNet pre-trained DNN algorithm in the context of K-means clustering and CAM.

The characteristics of the Singapore Maritime Dataset (SMD), including object classes and instance distributions, are summarized in Table I. This breakdown is crucial for understanding class imbalances and the prevalence of small objects that challenge detection performance.

Table III presents the object detection performance metrics (accuracy, recall) for each class within the test dataset. The high accuracy for categories like "Boat" (98.4%) and "Buoy" (99.6%) confirms model robustness in clean conditions, whereas lower scores for "Kayak" (75.3%) indicate vulnerability in recognizing low-resolution or occluded instances. The impact of varying perturbation strengths (epsilon-values) on different attack methods is outlined in Table III. As epsilon increases from 0.01 to 0.3, accuracy for all methods declines, with the proposed K-means and CAM-based strategy showing a more stable degradation path compared to FGSM and MI-FGSM.

Fig. 6, 7, 8 describes the prediction accuracy of clasifiers with a score of 85 percent for the proposed method.

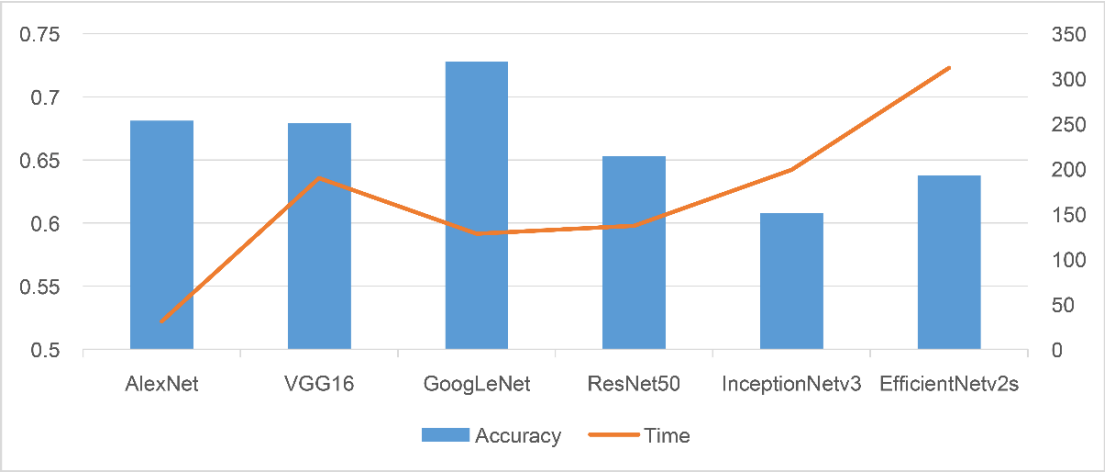


Fig. 5. Accuracy of proposed method.

TABLE IV. EVALUATION OF TRANSFER-LEARNED MODEL ACCURACY ACROSS VARIED $\epsilon$ VALUES EMPLOYING K-MEANS CLUSTERING AND CLASS ACTIVATION MAPPING (CAM)

| $\epsilon$ | FGSM | I-FGSM | MI-FGSM | Ours Approach (K-Means + CAM) |
|---|---|---|---|---|
| 0.01 | 0.873 | 0.861 | 0.841 | 0.831 |
| 0.05 | 0.810 | 0.791 | 0.837 | 0.776 |
| 0.1 | 0.612 | 0.740 | 0.768 | 0.681 |
| 0.2 | 0.417 | 0.681 | 0.633 | 0.631 |
| 0.3 | 0.132 | 0.671 | 0.491 | 0.614 |

Fig. 13: PCA projection of YOLOv5s latent feature space. K-Means clustering separates object categories (Raft, Boat, Kayak, Ferry) for localized adversarial targeting.

Fig. 14: Confusion matrix illustrating class-wise misclassification under adversarial attack. Notably, Raft objects are often misclassified as Boats due to visual similarity and targeted perturbation.

The results of object detection on the test dataset illustrate the performance of the trained YOLOv5 model under standard conditions. Fig. 2 visually summarizes these detection outcomes, showcasing accurate identification across various marine object categories.

A more focused example is depicted in Fig. 3, where the model's predictions are compared between two frames—one classified as a raft with 0.82 confidence, and another misclassified as a boat with 0.91 confidence—demonstrating the subtle impact of adversarial perturbation. Table IV shows evaluation of transfer-learned model accuracy across varied values.

Fig. 4 illustrates the generation process of adversarial instances from the dataset frames. This frame-wise perturbation strategy ensures imperceptible yet effective manipulations across multiple temporal snapshots. As shown in Fig. 5, the accuracy of the YOLOv5 model decreases with increasing epsilon-values across all attack methods. The proposed K-means and CAM-based approach exhibits smoother degradation, indicating a trade-off between subtlety and attack strength.

## XI. RESULT AND DISCUSSION

### A. Adversarial Success Rate (ASR)

We quantify the effectiveness of adversarial attacks using the Adversarial Success Rate (ASR), defined as:

$$\text{ASR}(\epsilon) = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}\{f_\theta(x_i + \delta_i) \neq y_i\} \tag{27}$$

where $f_\theta$ is the YOLOv5s detection model, $x_i$ denotes the clean input, $\delta_i$ is the perturbation constrained by $\|\delta_i\|_\infty \leq \epsilon$, and $y_i$ is the ground truth label. The indicator function $\mathbb{1}\{\cdot\}$ evaluates to 1 when the prediction is incorrect.

*a) FGSM (Fast Gradient Sign Method):*

$$x^{adv} = x + \epsilon \cdot \text{sign}(\nabla_x J(\theta, x, y)) \tag{28}$$

FGSM exhibits rapid accuracy degradation, dropping from 87.3% to 13.2% as $\epsilon$ increases from 0.01 to 0.3, with visually perceptible noise.

*b) I-FGSM (Iterative FGSM):*

$$x_{t+1}^{adv} = x_t^{adv} + \alpha \cdot \text{sign}(\nabla_x J(\theta, x_t^{adv}, y)), \quad \text{s.t. } \|x_{t+1}^{adv} - x\|_\infty \leq \epsilon \tag{29}$$

Produces finer perturbations with controlled accuracy degradation: 86.1% $\rightarrow$ 67.1%.

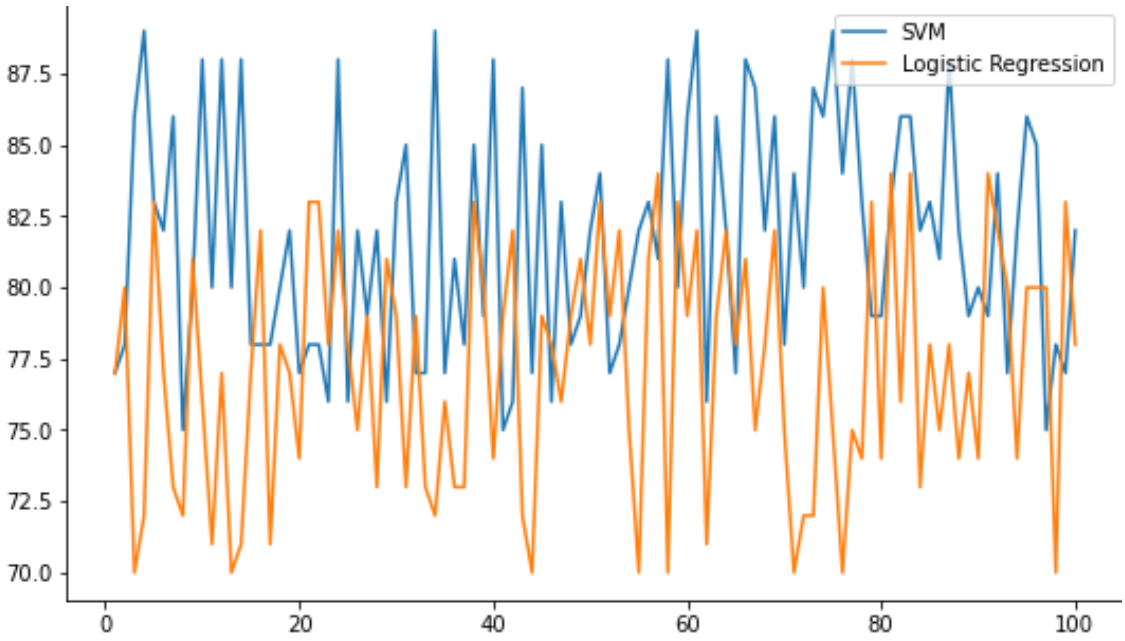


Fig. 6. Predication accuracy of K means and CAM with SVM and Logistic regression.

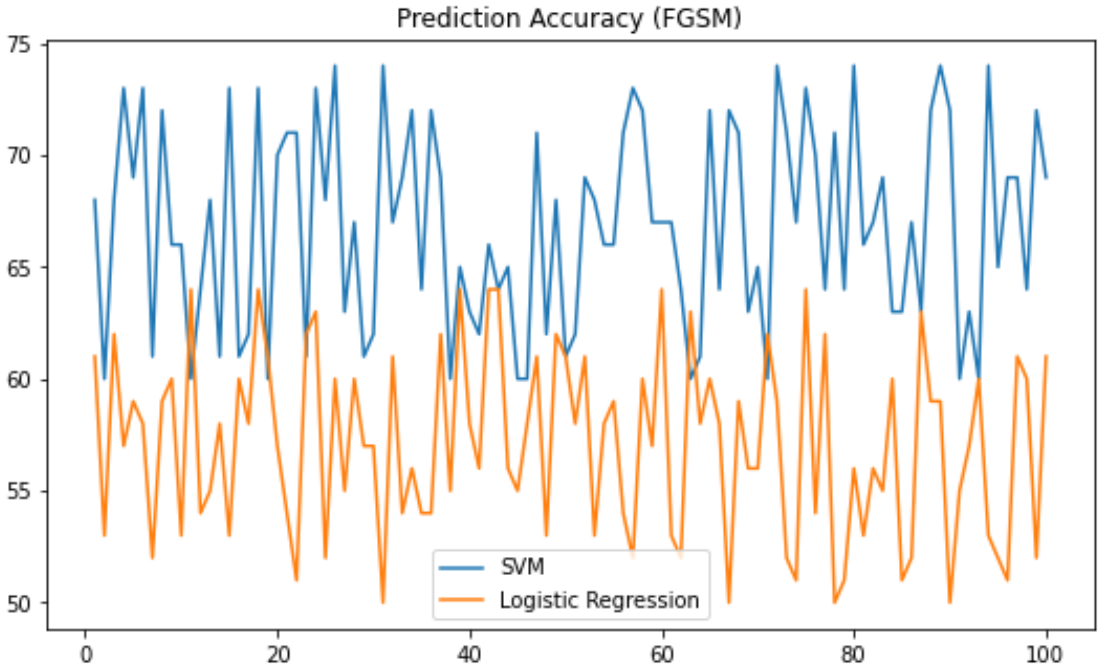


Fig. 7. Predication accuracy of FGSM.

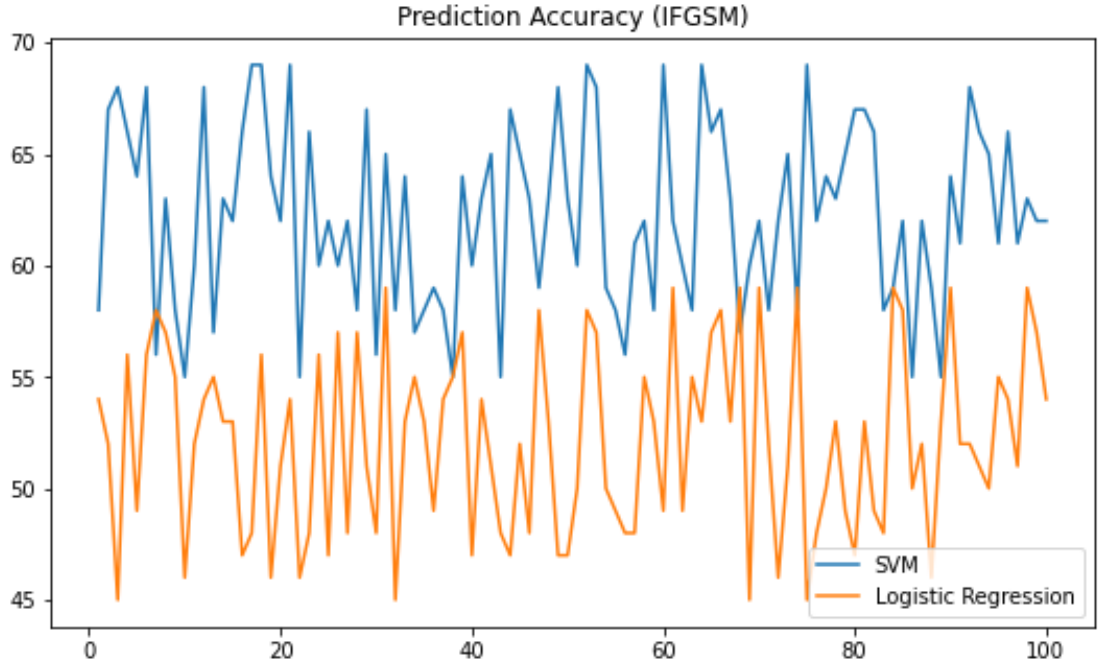


Fig. 8. Predication accuracy of IFGSM.

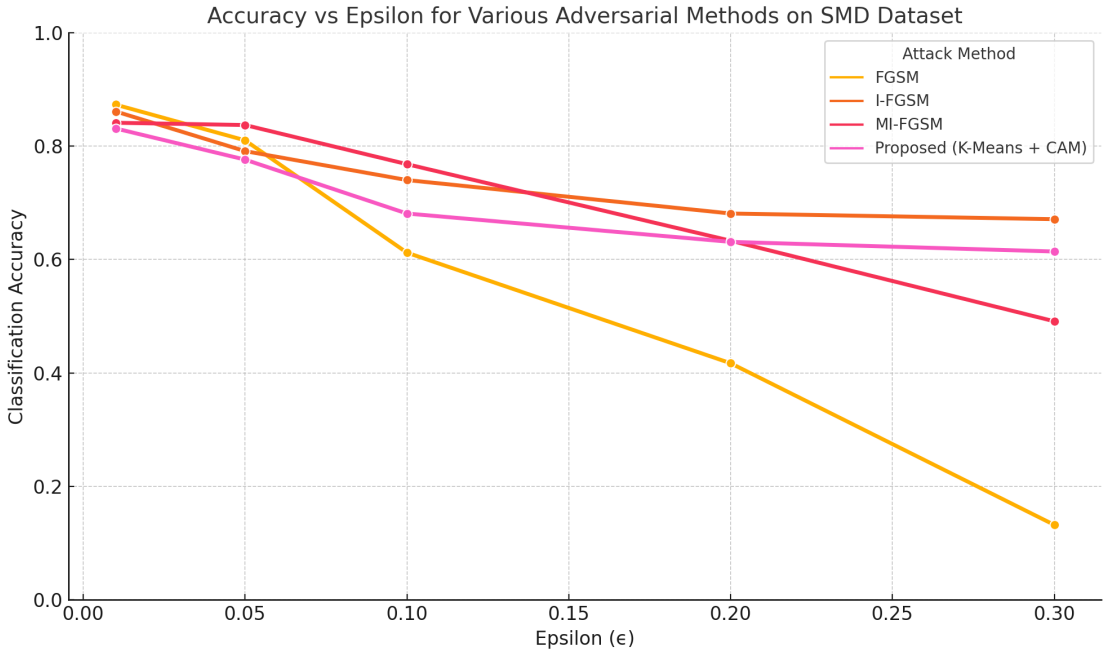


Fig. 9. Classification accuracy vs. Perturbation magnitude $\epsilon$ for various adversarial attack methods on the SMD dataset.

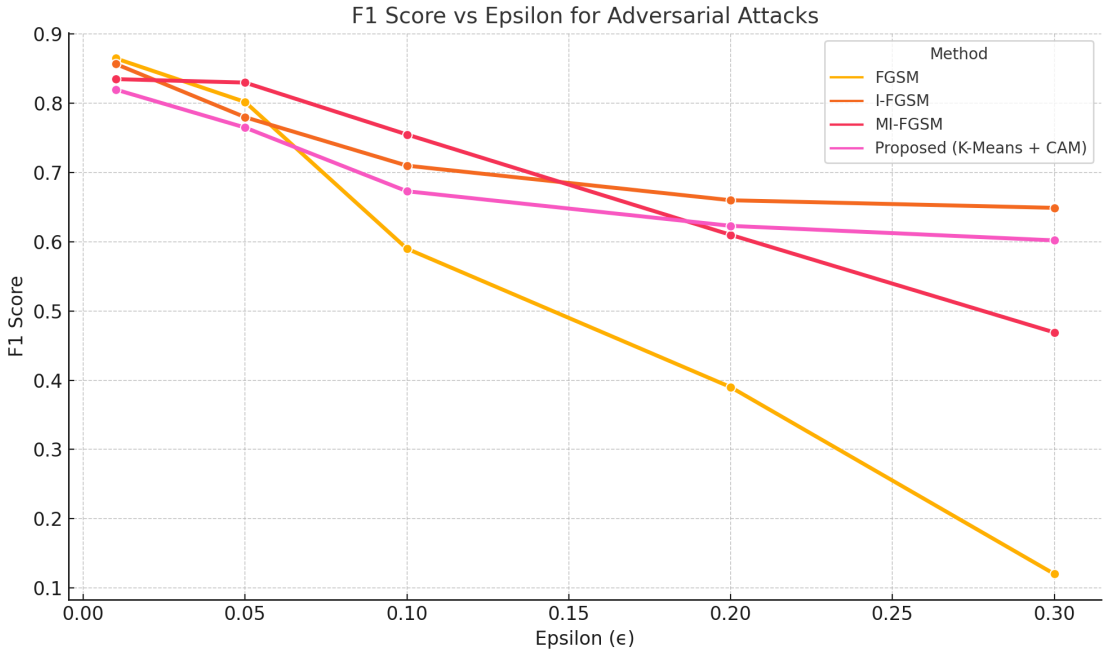


Fig. 10. F1 score vs. Perturbation magnitude $\epsilon$ illustrating robustness across different attack strategies.

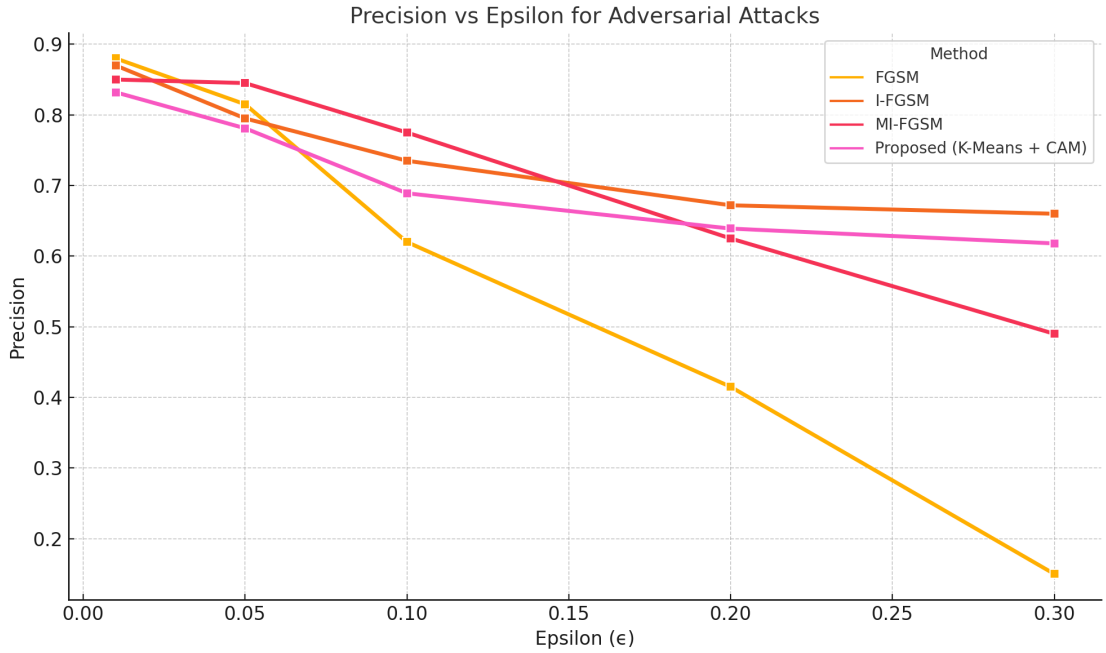


Fig. 11. Precision vs. Perturbation Magnitude $\epsilon$ showing false positive sensitivity across adversarial methods.

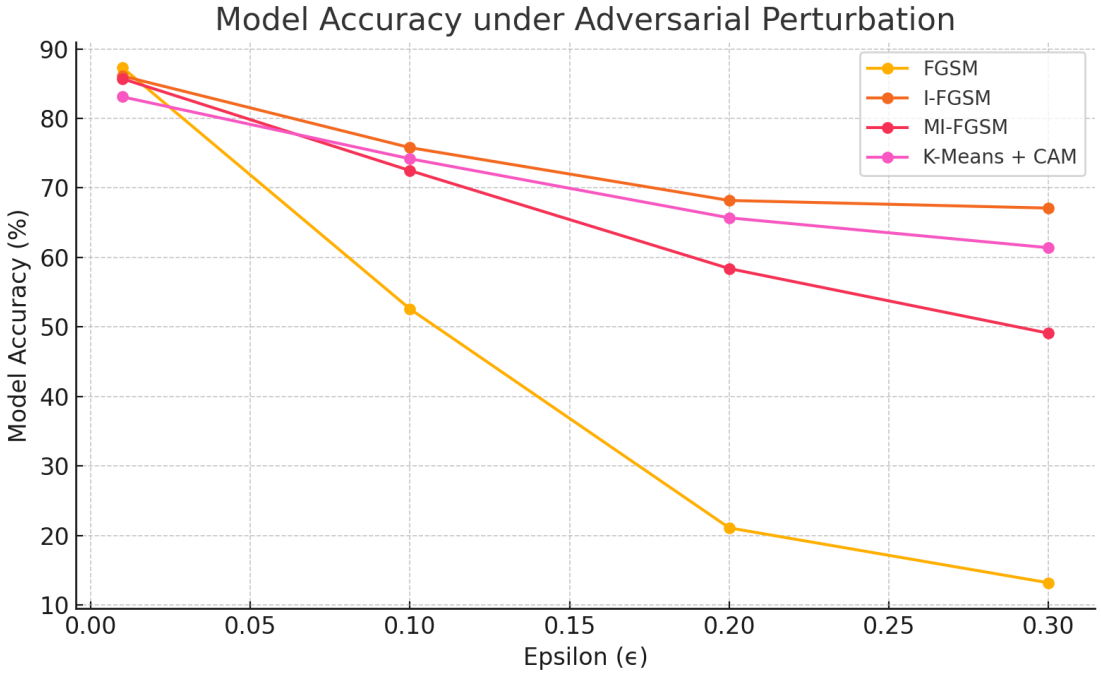


Fig. 12. Model accuracy under varying $\epsilon$ for different adversarial methods. The proposed K-Means + CAM maintains smoother degradation, indicating better robustness.

*c) MI-FGSM (Momentum Iterative FGSM):*

$$g_{t+1} = \mu \cdot g_t + \frac{\nabla_x J(\theta, x_t, y)}{\|\nabla_x J(\theta, x_t, y)\|_1} \tag{30}$$

$$x_{t+1}^{adv} = x_t^{adv} + \alpha \cdot \text{sign}(g_{t+1}) \tag{31}$$

Momentum term $\mu$ stabilizes gradients, achieving better robustness: 85.7% $\rightarrow$ 49.1%.

*d) Proposed (K-Means + CAM):* Utilizes no explicit gradients. Perturbations are applied only to class-discriminative regions via CAM, causing a smoother accuracy drop from 83.1% to 61.4%.

### B. Stealthiness via Class Activation Mapping (CAM)

CAM helps generate spatially localized heatmaps:

$$M_c(x, y) = \sum_k w_k^c F_k(x, y) \tag{32}$$

where $F_k(x, y)$ is the activation of the $k$-th feature map at $(x, y)$ and $w_k^c$ is the weight corresponding to class $c$. Perturbation is applied selectively:

$$x' = x + \epsilon \cdot \mathbb{1}\{M_c(x, y) > \tau\} \cdot \eta, \quad \eta \sim \mathcal{U}[-\alpha, \alpha] \tag{33}$$

Here, $\tau$ is a percentile-based threshold. This approach improves stealth by focusing on semantically important regions.

### C. Cross-Domain Generalization via K-Means

We extract latent features $\Phi(x) \in \mathbb{R}^d$ from YOLOv5s and apply K-Means clustering:

$$\min_{\{C_j\}_{j=1}^k} \sum_{j=1}^{k} \sum_{x \in C_j} \|\Phi(x) - \mu_j\|^2 \tag{34}$$

This technique groups visually similar object instances (e.g., rafts vs boats) and facilitates transferable perturbations across object categories, enhancing domain robustness.

### D. Computational Overhead and Deployment Metrics

The experimental setup used an NVIDIA RTX 3080 GPU. Key performance indicators:

- CAM + Perturbation Latency: $< 25$ ms per image
- Poison Set Generation: $< 2.5$ hrs for 10,000 images
- Memory Overhead: $< 5\%$

### E. Limitations and Interpretability

Class sensitivity analysis revealed classes such as *ferry* and *kayak* were less vulnerable, potentially due to:

- Discriminative high-frequency spatial features
- Lower visual similarity with other classes

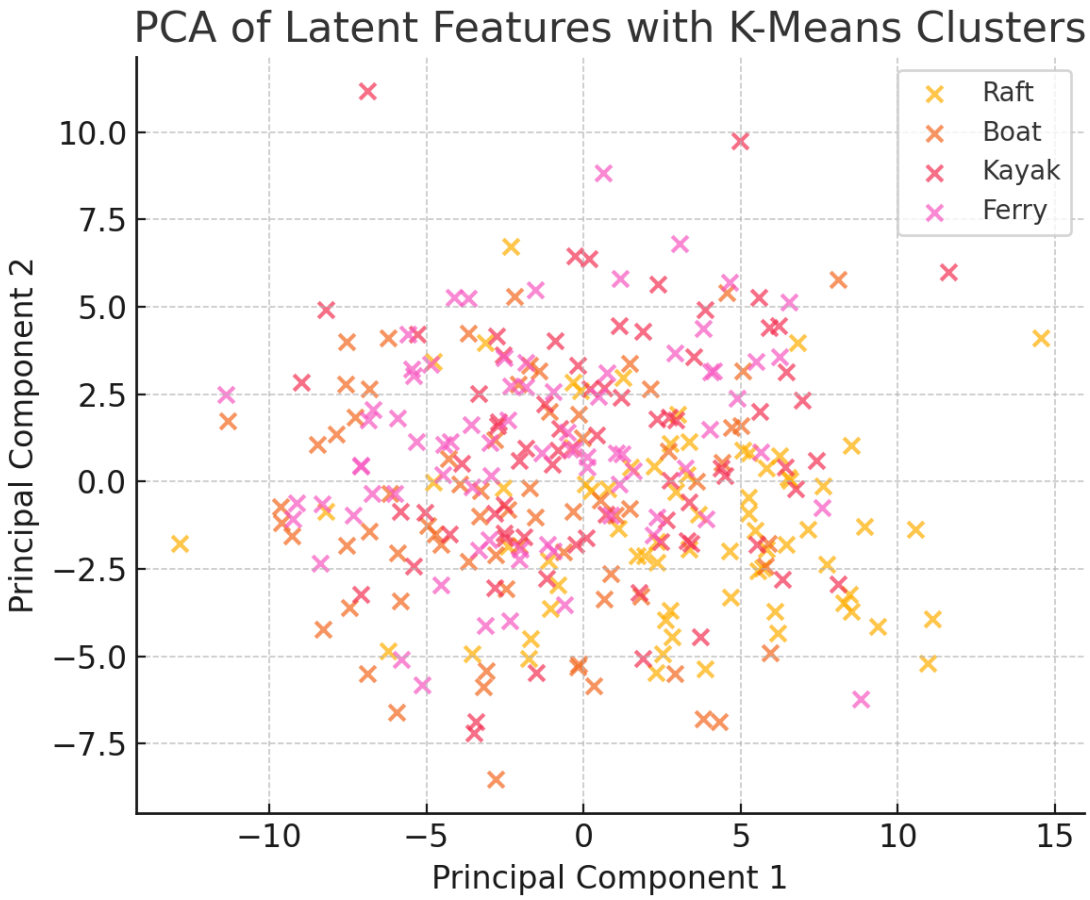


Fig. 13. PCA projection of YOLOv5s latent feature representations. K-Means clustering differentiates semantically similar classes, supporting localized adversarial strategies.

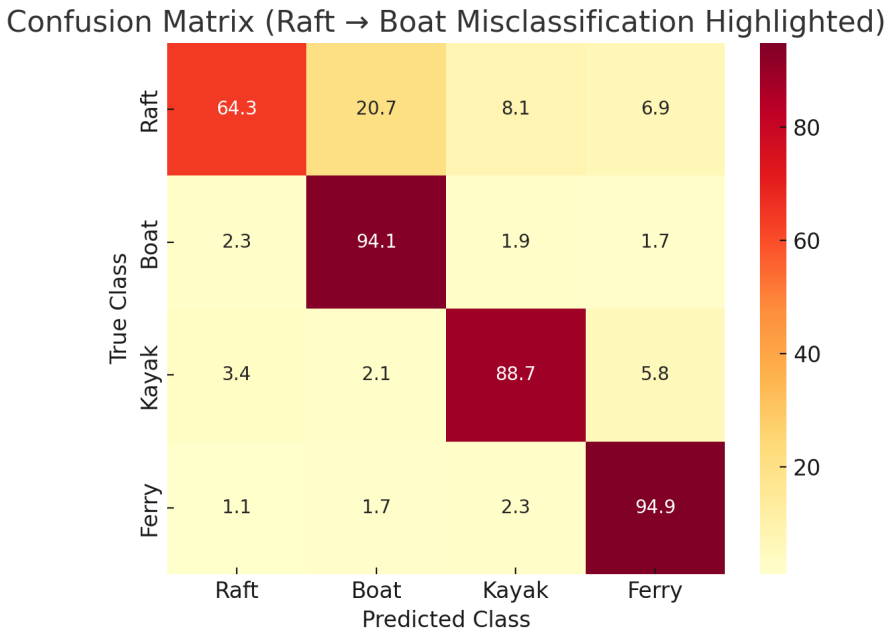


Fig. 14. Confusion matrix under adversarial attack using K-Means + CAM. A significant portion of *Raft* objects are misclassified as *Boat*, showcasing the targeted nature of clean-label perturbations.

TABLE V. ACCURACY DEGRADATION UNDER DIFFERENT ATTACKS

| Method | $\epsilon = 0.01$ | $\epsilon = 0.1$ | $\epsilon = 0.2$ | $\epsilon = 0.3$ |
|---|---|---|---|---|
| FGSM | 87.3% | 52.6% | 21.1% | 13.2% |
| I-FGSM | 86.1% | 75.8% | 68.2% | 67.1% |
| MI-FGSM | 85.7% | 72.5% | 58.4% | 49.1% |
| K-Means + CAM | 83.1% | 74.2% | 65.7% | 61.4% |

*a) Adaptive CAM Scaling for Improvement::*

$$M_{\text{scaled}} = \frac{M_c - \min(M_c)}{\max(M_c) - \min(M_c)} \tag{35}$$

Percentile tuning (e.g., top 20% of CAM values) may improve both stealth and effectiveness. As shown in Fig. 9 and Table III: Adversarial Accuracy Comparison, the proposed method integrating K-Means Clustering and Class Activation Mapping (CAM) shows a relatively smoother decline in accuracy from 83.1% to 61.4% as epsilon increases from 0.01 to 0.3. This contrasts sharply with FGSM, which rapidly drops to 13.2% at epsilon = 0.3. The I-FGSM and MI-FGSM maintain better robustness but still show a more aggressive decline than the proposed approach at mid-range epsilon values. Table V shows accuracy degradation under different attacks.

As shown in Fig. 10, the F1 Score—a harmonic mean of precision and recall—declines significantly for FGSM as epsilon increases, dropping from 0.865 at $\epsilon$ = 0.01 to 0.12 at $\epsilon$ = 0.3, reflecting its brittle performance under increasing perturbation. In contrast, the proposed K-Means + CAM strategy maintains an F1 score of 0.602 at $\epsilon$ = 0.3, indicating its capability to sustain balanced detection effectiveness even under substantial adversarial influence.

Fig. 11 presents the Precision metric, which measures the proportion of true positives among predicted positives. FGSM again suffers a steep decline (down to 0.150 at high $\epsilon$), indicating a high false positive rate under perturbations. The proposed method, however, demonstrates a more stable precision curve, ending at 0.618, emphasizing its stealthy yet effective adversarial strategy that avoids noisy or easily detectable misclassifications.

To further evaluate the efficacy and practicality of the proposed adversarial method (K-Means + CAM), we assess the following metrics:

*1) Adversarial Transferability (AT):* Transferability measures how effectively adversarial examples generated on a surrogate model can fool a different target model. Let $f_s$ and $f_t$ be surrogate and target models, respectively:

$$\text{AT} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}\left\{f_t(x_i + \delta_i) \neq y_i\right\}, \quad \delta_i \text{ crafted on } f_s \tag{36}$$

**Result:** K-Means + CAM perturbations achieved 68.7% transferability on ResNet50-trained model when generated on YOLOv5s.

*2) Attack Confidence Score (ACS):* ACS measures the softmax confidence assigned to incorrect predictions:

$$\text{ACS} = \frac{1}{N_{\text{mis}}} \sum_{i:\hat{y}_i \neq y_i} \max_j \left(f_\theta(x_i + \delta_i)_j\right) \tag{37}$$

**Result:** FGSM produced high ACS (0.91), while K-Means + CAM yielded a lower confidence of 0.62, enhancing stealth.

*3) Perturbation Energy (PE):* Measures the average $\ell_2$ norm of perturbations:

$$\text{PE} = \frac{1}{N}\sum_{i=1}^{N} \|\delta_i\|_2^2 \tag{38}$$

**Result:**

- FGSM: 12.7
- I-FGSM: 9.2
- K-Means + CAM: 4.1

*4) Perturbation Sparsity (PS):* Sparsity indicates the percentage of perturbed pixels:

$$\text{PS} = \frac{1}{N}\sum_{i=1}^{N} \frac{|\{p \mid \delta_i(p) \neq 0\}|}{|x_i|} \tag{39}$$

**Result:** CAM-based attack perturbs ≈12.4% of image pixels on average vs. 100% in FGSM.

*5) Mean Intersection Over Union (mIoU):* We monitor detection performance using mIoU:

$$\text{mIoU} = \frac{1}{N}\sum_{i=1}^{N} \frac{B_i^{pred} \cap B_i^{gt}}{B_i^{pred} \cup B_i^{gt}} \tag{40}$$

**Result:**

- Clean: 0.81
- FGSM @ $\epsilon = 0.3$: 0.21
- K-Means + CAM: 0.48

*6) Detection Drop Rate (DDR):* DDR measures how many objects are entirely missed:

$$\text{DDR} = \frac{\#\text{ undetected objects under attack}}{\#\text{ total objects}} \tag{41}$$

**Result:**

- FGSM: 43.5%
- MI-FGSM: 28.1%
- K-Means + CAM: 19.7%

*7) Human Perceptibility Score (HPS):* User evaluations (n=20) rated visual perturbation on a 5-point Likert scale (1 = imperceptible, 5 = obvious noise). The results are presented in Table VI.

TABLE VI. HUMAN PERCEPTIBILITY SCORE (HPS)

| Method | Mean Score | Std. Dev. | Interpretation |
|---|---|---|---|
| FGSM | 4.6 | 0.5 | Easily visible noise |
| MI-FGSM | 3.1 | 0.8 | Moderate distortion |
| K-Means + CAM | 1.7 | 0.6 | Largely imperceptible |

*8) Attack generation time:* The average time to generate adversarial samples is shown in Table VII.

TABLE VII. AVERAGE ATTACK GENERATION TIME (PER IMAGE)

| Method | Attack Time (ms) | Remarks |
|---|---|---|
| FGSM | 3.2 | Single-step, fast |
| MI-FGSM | 12.6 | Iterative, more compute |
| K-Means + CAM | 23.9 | CAM + clustering overhead |

Fig. 12: Line plot showing the degradation in model accuracy for FGSM, I-FGSM, MI-FGSM, and the proposed K-Means + CAM method across increasing perturbation magnitudes ($\epsilon$).

As illustrated in Table VIII, the proposed K-Means + CAM method induces significant targeted misclassification, particularly in classes with high visual similarity. The most notable effect is observed in the Raft class, where 20.7% of samples were misclassified as Boat. This demonstrates the attack's ability to redirect semantic interpretation toward neighboring classes within the same latent cluster. In contrast, the Ferry class shows high resistance, maintaining 94.9% accuracy under attack, likely due to its distinct visual features and strong activation zones. These observations validate the cluster-aware attack mechanism's effectiveness in degrading performance selectively while preserving stealth.

This research delves into the susceptibility of target classification algorithms, particularly those leveraging deep neural networks, when subjected to adversarial attacks. Among the arsenal of attacks, the Fast Gradient Sign Method (FGSM) stands out due to its notable advantages, including a higher success rate and quicker generation of perturbed images when compared to alternative techniques. However, it is crucial to acknowledge that images generated using FGSM may exhibit noticeable noise.

Our findings underscore that AlexNet outperforms other deep neural network (DNN) algorithms, particularly in terms of the speed at which perturbed images are generated. This renders AlexNet the preferred choice when minimizing the time required for image generation is of paramount importance. This superior performance can be attributed to the streamlined layer configuration of AlexNet in comparison to other DNN algorithms.

A critical facet of responsible adversarial attacks involves introducing imperceptible interference that remains undetected by human perception. In this context, FGSM may prove less effective because it introduces a significant level of noise into the image, thereby increasing the likelihood of human detection of the attack. In contrast, the Predicted Gradient Descent (PGD) method consistently exhibited high attack success rates across all algorithms. Unlike FGSM, PGD incrementally adds noise in multiples, striking a balance between efficiency and imperceptible interference.

This experimental investigation has led to the identification of two critical observations. Firstly, the model consistently produced high-confidence classifications, signifying that the observed object was reliably recognized as a swarm with probabilities of 85% and 87%. Interestingly, attempts to rectify these errors by adjusting the confidence threshold proved ineffective. Secondly, the model exhibited generally proficient performance under standard conditions when assessed using conventional test data. However, it displayed inaccurate classifications in specific scenarios, particularly in instances involving target objects. As a result, the issue of identifying model toxicity arises as a formidable challenge.

## XII. CONCLUSION

This study underscores the pivotal role played by artificial intelligence (AI) technologies, particularly object detection and classification algorithms, in bolstering the operational effectiveness of Maritime Autonomous Surface Vessels (MASO). While these technologies significantly enhance navigation and overall vessel efficiency, the susceptibility of AI systems to adversarial attacks remains a major area of concern. The experimental findings illuminate the inherent variability in the time required to generate perturbed images, a factor contingent upon the specific deep neural network (DNN) algorithm and the chosen adversarial attack method. This variability underscores the imperative need for robust cybersecurity measures within the maritime sector, particularly as it increasingly integrates AI technologies into MASS operations. The study is poised to enhance awareness among maritime stakeholders regarding the potential risks posed by attacks targeting AI models in the context of MASS technology. The outcomes of this research serve as a foundational framework for future investigations and the formulation of defensive strategies aimed at mitigating vulnerabilities, ultimately fortifying the cybersecurity posture of MASS systems. Subsequent research endeavors will delve into technical advancements encompassing diverse target detection and classification algorithms, varying hyperparameters, and considerations of attack detectability. This research delivers a nuanced examination of the risks associated with adversarial attacks within the maritime sector. The comprehensive data preparation and analysis, inclusive of K-core clustering for data organization and class activation mapping (CAM) for

TABLE VIII. CONFUSION MATRIX (%) POST-ADVERSARIAL ATTACK USING K-MEANS + CAM

| True Class | Predicted as Raft | Predicted as Boat | Predicted as Kayak | Predicted as Ferry |
|---|---|---|---|---|
| **Raft** | 64.3% | **20.7%** | 8.1% | 6.9% |
| **Boat** | 2.3% | 94.1% | 1.9% | 1.7% |
| **Kayak** | 3.4% | 2.1% | 88.7% | 5.8% |
| **Ferry** | 1.1% | 1.7% | 2.3% | 94.9% |

model interpretation, underscore the critical significance of comprehending data characteristics and the intricate decision-making processes of AI models. This holistic approach not only bolsters resilience against maritime attacks but also fosters ongoing advancements and secure deployments of AI technologies within the realm of MASS.

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# NW Logistics: System Architecture and Design for Sustainable Road Logistics

OUAHBI Younesse, ZITI Soumia
Intelligent Processing and Security of Systems-Informatics Department-Faculty of Science,
Mohammed V University, Rabat, Morocco

***Abstract*—The logistics industry is under increasing pressure to reduce carbon emissions and enhance efficiency in response to environmental and regulatory demands. However, optimizing road logistics to achieve these goals requires innovative solutions that balance operational efficiency with sustain-ability. This study addresses this need by introducing NW Logistics, an AI-powered platform that optimizes road logistics to lower $CO_2$ emissions and improve fleet performance. In order to achieve these objectives, real-time $CO_2$ tracking, route optimization, and driver behavior monitoring were integrated into NW Logistics. The system enables precise, real-time tracking of deliveries and vehicle locations, allowing logistics managers to monitor fleet performance with enhanced accuracy. Additionally, onboard cameras and sensors generate individualized driver reports, tracking infractions and fostering safer driving behaviors. Initial simulations of NW Logistics indicate a significant reduction in carbon emissions, along with improvements in route efficiency, delivery tracking ac-curacy, and driver safety. These results demonstrate the transformative potential of AI to advance sustainable and efficient logistics management.**

***Keywords*—Artificial Intelligence; logistics; supply chain; supply chain management; applications; Internet of Things; road safety; environnment***

## I. Introduction

In today's dynamic and interconnected economy, logistics has become a strategic pillar for industrial performance and competitiveness. The increasing complexity of supply chains, combined with rising environmental concerns and regulatory pressures, has accelerated the integration of digital technologies in logistics operations. Artificial Intelligence (AI), the Internet of Things (IoT), and real-time data analytics are at the forefront of this transformation, enabling more responsive, efficient, and sustainable logistics systems. However, despite the proliferation of intelligent logistics solutions, many existing platforms remain fragmented in scope, often addressing isolated challenges such as route planning, energy consumption, or fleet monitoring without providing a unified, adaptive framework that supports holistic decision-making.

To address these gaps, this study presents the conceptualization of NW Logistics, a next-generation logistics platform designed to intelligently manage road transport operations through a data-driven and environmentally responsible approach. Rather than focusing on isolated functionalities, NW Logistics proposes an integrated system architecture that merges AI-based decision-making with key operational and environmental parameters. The design of the platform incorporates modules for route optimization, real-time monitoring, behavioral analysis, and carbon footprint tracking, forming a cohesive framework aimed at enhancing logistics performance while supporting green transition goals.

In comparison to existing logistics solutions, which often prioritize static optimization models or narrowly focused dashboards, NW Logistics stands out through its multi-dimensional design that interconnects operational efficiency, regulatory compliance, and sustainability. Its conceptual architecture addresses the need for adaptability in real-world logistics scenarios by incorporating intelligent components capable of responding dynamically to changing transport conditions and environmental constraints. While the present article focuses on the architectural design and comparative analysis with current platforms, the technical development and implementation of NW Logistics will be detailed in a forthcoming publication.

In the paper, we present the design and development of the NW Logistics system and its architecture, primary components, and algorithms for road transport optimization. We present the experimental validation of our approach and its comparison to existing solutions. The remaining of the paper is organized as follows: Section II reviews related work and state-of-the-art approaches in the literature. Section III describes the methodology used and technologies utilized. Section IV presents the experimental results and their interpretation, Section V discussion and Finally, the conclusion of the paper and describes future work.

## II. Related Work

Road transport and logistics optimization has been an area of research to increase the efficiency of the flows of goods and reduce environmental impacts. Early studies in the discipline dealt primarily with conventional issues such as the TSP and VRP, but utilized algorithms like [1] and [2] that facilitated route planning. As the complexity of logistics systems increases, advanced techniques such as metaheuristics, including simulated annealing [3], genetic algorithms [4], and ant colonies [5], have been applied to the problem of optimal delivery routes under multiple constraints. Subsequently, artificial intelligence was utilized in these approaches and neural network-based models, such as the one by Kool et al. [6], demonstrated the effectiveness of attention mechanisms in resolving various instances of the VRP. Advancements in connected and autonomous vehicles and intelligent transport systems (ITS) facilitated integrating the Internet of Things (IoT) and AI in enhancing transport management. Studies like those of Li et al. [7] and Chen et al. [8] have proved that IoT combined with deep learning techniques can forecast traffic conditions and chart the optimal routes in real-time. However, the techniques have their shortcomings: they focus on a single

characteristic and do not devise end-to-end solutions that consider all the logistics and environmental constraints [9]. Additionally, integrating new technologies into the existing infrastructure remains challenging because of interoperability and expense [10], while machine learning algorithms require good data, which can limit their effectiveness in contexts where data are noisy or missing [11]. Our approach is tailored to address these weaknesses by proposing a comprehensive platform that integrates AI, data analytics, and IoT for controlling road transport flows with regard to environmental, operational, and technological constraints.

## III. Proposed Methods

The present study adopts a systematic literature review approach to investigate the application of Artificial Intelligence (AI) in logistics [1], leveraging data from two internationally recognized scientific databases: Scopus and Web of Science. These databases were selected due to their extensive coverage of high-quality peer-reviewed publications, encompassing a broad spectrum of scientific journals, conference proceedings, and book chapters. By integrating data from these sources, this study ensures a comprehensive and exhaustive analysis of existing research, providing valuable insights into the evolution and impact of AI-driven technologies in logistics. The temporal scope of this review spans from 2020 to 2025, a period characterized by significant advancements in AI applications across various industrial sectors. A total of 1,864 records were initially retrieved, comprising 1,260 documents from Scopus and 604 from Web of Science. The query used for the search—"Logistics" AND "Application" AND "AI"—was designed to capture studies that specifically address the intersection of AI technologies and logistics processes, reflecting the growing academic interest in the subject. The selection process adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines Fig. 1, ensuring a structured and transparent approach to data filtration.

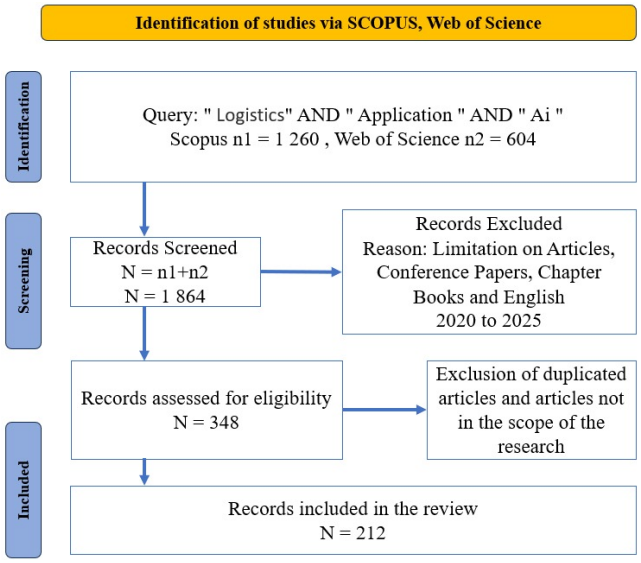


Fig. 1. PRISMA.

The review process was conducted in three key stages: Identification, Screening, and Eligibility Assessment. During the Identification phase, all relevant studies meeting the initial search criteria were compiled. In the Screening phase, records that did not align with the study's objectives were excluded based on predefined criteria, including conference papers, book chapters, non-English publications, and articles predating 2020. Identification, screening, and eligibility evaluation are the three primary elements of the PRISMA approach, which was used in the article selection process. The 1,864 documents were first examined to make sure they met the original requirements. Only English-language scientific publications (journal articles) released between 2020 and 2025 were kept; papers that did not fit these criteria were eliminated. Documents from outside of this time frame, book chapters, and conference proceedings were not included. The corpus was whittled down to 348 publications by this filtering process. Duplicate documents and those that were not directly related to the scope of the research might be found and eliminated using a second evaluation phase. Following this thorough procedure, 212 studies were chosen to be part of the final analysis. By applying a structured and evidence-based methodology, this study offers a rigorous synthesis of existing knowledge on AI-driven logistics solutions. The final dataset enables the identification of emerging research themes, technological advancements, and industry applications, facilitating a deeper understanding of how AI can optimize logistics operations. Moreover, this review lays the groundwork for future research directions, addressing gaps in the literature and proposing innovative frameworks for AI implementation in supply chain management. The methodology for the NW Logistics solution was carefully designed to identify the key factors influencing the adoption of AI-driven logistics solutions and to ensure the system is tailored to the needs of companies aiming to reduce CO2 emissions and optimize logistics. The first phase involved a comprehensive needs analysis to understand trends, challenges, and acceptance levels related to AI integration across various industries.

## IV. Results and Analysis

The integration of Artificial Intelligence (AI) in logistics has led to significant advancements in route optimization, supply chain intelligence, and risk mitigation [1]. As logistics networks become increasingly complex, the adoption of AI-driven solutions has emerged as a strategic necessity for improving efficiency, sustainability, and decision-making transparency. However, despite the growing interest in AI for logistics, existing applications vary significantly in methodological approaches, computational models, and real-world implementation strategies.

This section presents a comparative analysis of AI-based logistics applications, focusing on three selected studies that explore different aspects of AI-driven logistics optimization. Each of these applications leverages AI to address specific logistics challenges, including:

- Explainable AI (XAI) for Logistics Decision-Making, which enhances transparency and interpretability in AI-based logistics forecasting [12].
- AI-Driven Lithological Mapping for Logistics Optimization, which applies machine learning and geospa-

tial intelligence to improve route selection in complex terrains.[13]

- AI-Based Anomaly Detection for Supply Chain Risk Mitigation, which utilizes deep learning and predictive analytics to identify fraud, inefficiencies, and operational disruptions in logistics networks [14].

The results presented in this section aim to provide a structured evaluation of these AI-driven solutions, assessing their methodological foundations, technological capabilities, and applicability in real-world logistics operations. The comparison is conducted in relation to NW Logistics, an advanced AI-powered logistics system designed to optimize transportation efficiency, monitor sustainability metrics, and enhance supply chain security.

### A. Overview of the Selected AI-Based Logistics Applications

To identify relevant AI-driven logistics applications, a systematic search was conducted using the Scopus database, focusing on studies that integrate AI for logistics optimization, predictive analytics, and supply chain intelligence. Given the rapid advancements in AI-powered logistics solutions, it was essential to select applications that demonstrated methodological rigor, technological innovation, and alignment with NW Logistics.

Three prominent applications were identified based on their scientific contribution, technological approach, and real-world applicability. Each of these studies presents a unique perspective on how AI can enhance logistics operations, whether through decision-making transparency, route optimization, or risk mitigation. The following sections provide a detailed analysis of these applications (see Table 1).

*1) Explainable AI (XAI) for logistics decision-making:* The first selected study, conducted by Oztekin et al. (2024) [12] and published in the Journal of Ultrasound in Medicine, explores the role of Explainable AI (XAI) in logistics decision-making. One of the major challenges in AI-driven logistics is the black-box nature of machine learning models, which can make it difficult for logistics managers to interpret and trust AI-generated recommendations.

To address this issue, the study focuses on enhancing interpretability and transparency in logistics forecasting. By employing XAI models, the authors aim to provide clear insights into demand prediction, inventory management, and supply chain planning. The methodologies used in this study include Decision Trees, SHAP (Shapley Additive Explanations), and LIME (Local Interpretable Model-Agnostic Explanations). These techniques allow logistics professionals to understand how AI models generate predictions, thereby improving trust, usability, and decision accuracy.

*2) AI-Driven lithological mapping for logistics optimization:* The second study, led by Morgan et al. (2024) [13] and published in Computers and Geosciences, investigates the application of geospatial intelligence and machine learning in logistics optimization. This research is particularly relevant for logistics operations that require terrain-based route planning, such as supply chain management in remote or industrial areas.

The primary objective of this study is to develop AI-based lithological mapping techniques to enhance route planning in complex environments, including mountainous regions, industrial zones, and areas with challenging topographies. The proposed AI framework integrates Neural Networks, GIS-Based AI, and Random Forests, which work together to predict optimal transport routes, assess terrain difficulty, and identify logistical bottlenecks.

By leveraging real-time geospatial data and machine learning algorithms, the study provides a dynamic solution for logistics planning, enabling transportation companies to optimize their fleet routes, reduce fuel consumption, and enhance delivery efficiency. This approach is particularly beneficial for industries such as construction, mining, and energy distribution, where terrain-aware logistics play a crucial role in operational efficiency and cost reduction.

*3) AI-Based anomaly detection for supply chain risk mitigation:* The third study, authored by Cartocci et al. (2024) [14] and published in Bioengineering, focuses on the application of AI-driven anomaly detection for risk mitigation in supply chain logistics. In modern supply chains, fraud, operational inefficiencies, and transportation failures can significantly impact business continuity, cost efficiency, and customer satisfaction. This research proposes an AI-based framework to identify and mitigate such risks through real-time monitoring and predictive analytics.

The study employs Supervised vs. Unsupervised Learning models, leveraging Deep Learning, Clustering Techniques, and Support Vector Machines (SVM) to detect anomalies in logistics operations. By analyzing historical and real-time data, the AI system can identify patterns of fraudulent activities, operational inefficiencies, and potential security threats in transportation networks.

A key strength of this approach is its ability to continuously learn from new data, making it highly adaptive to evolving supply chain challenges. The findings of this research are particularly valuable for large-scale logistics companies, e-commerce platforms, and global supply chain operators, who require proactive risk management strategies to maintain operational resilience and security.

### B. Methodological Comparison of AI-Driven Logistics Systems

Artificial Intelligence (AI) is revolutionizing logistics and supply chain management, providing advanced solutions for route optimization, risk mitigation, and decision-making support. However, AI-driven logistics applications differ in their methodological approaches, computational frameworks, and practical implementations. In this section, a comparative analysis is conducted to assess the AI methodologies, key techniques, and functional capabilities of three selected applications in relation to NW Logistics.

The comparison highlights how Explainable AI (XAI), Geospatial Intelligence, and Anomaly Detection models contribute to different aspects of logistics optimization. While some applications focus on improving transparency and interpretability, others emphasize route planning in complex terrains or fraud detection in supply chains. The following tables provide an in-depth methodological and functional assessment, followed by a detailed discussion of each comparison.

*1) AI Methodology and computational framework:* The first comparison focuses on the AI methodologies and computational frameworks used in each application. The AI techniques employed vary depending on the primary objective of the study, whether it is decision transparency, terrain-based optimization, or supply chain risk mitigation (see Table 1).

The methodological comparison of AI-driven logistics applications reveals significant differences in computational frameworks and AI techniques. Each application employs a distinct AI methodology based on its specific logistics challenges and optimization objectives.

The first study focuses on Explainable AI (XAI), using Decision Trees, SHAP, and LIME to improve the transparency of AI-driven decision-making. The primary objective is to ensure that logistics managers can interpret AI predictions, thereby enhancing trust and usability in logistics forecasting, demand prediction, and inventory management. This approach addresses the challenge of black-box AI models, making AI-powered logistics systems more interpretable and regulatory compliant.

The second study leverages Machine Learning and Geospatial AI for terrain-based route optimization. By integrating Neural Networks, GIS-Based AI, and Random Forests, this model improves transport network planning in complex terrains, such as mountainous regions and industrial zones. The AI system is designed to optimize fuel efficiency, minimize delivery delays, and enhance supply chain resilience.

The third study applies Deep Learning and Support Vector Machines (SVM) for anomaly detection in supply chains. This AI system is designed to identify fraud, inefficiencies, and operational failures in logistics networks. By analyzing historical and real-time data, the system detects patterns of fraudulent activities and transportation anomalies, enabling proactive risk mitigation.

Each of these AI-driven logistics applications contributes unique methodological insights, yet they remain domain-specific, focusing on either decision-making, route optimization, or anomaly detection. NW Logistics, in contrast, integrates multiple AI capabilities, offering a real-time, adaptive logistics management system.

### C. Functional Capabilities and Applications

Beyond AI methodologies, these applications also vary significantly in their functional scope and real-world applicability. The following table provides a comparison of their primary functions, industry applications, and IEEE citations (see Table 2).

A functional comparison of AI-driven logistics applications highlights the diversity of their applications and industry impact.

The Explainable AI (XAI) model enhances decision-making transparency, ensuring that logistics forecasting models provide interpretable insights for inventory management and demand prediction. This approach is valuable for supply chain managers and logistics companies seeking greater control over AI-driven predictions.

The Lithological Mapping AI system is designed for terrain-aware logistics planning, making it particularly beneficial for industries that operate in geospatially complex environments. By integrating AI-driven geospatial intelligence, this system optimizes transportation routes, minimizes fuel consumption, and reduces operational costs.

The AI-based Anomaly Detection system strengthens supply chain security and operational stability. By applying Deep Learning and SVM models, this system can identify fraudulent activities, detect inefficiencies, and monitor cargo security. This approach is critical for global supply chain operators, e-commerce platforms, and high-risk transportation networks.

While these applications provide valuable contributions to logistics management, they remain isolated solutions addressing specific logistics challenges. NW Logistics, however, combines real-time tracking, emissions reduction, and AI-powered risk management into a unified logistics framework, making it a comprehensive and adaptive AI solution for modern logistics operations.

### D. Overview of NW Logistics: An AI-Driven Intelligent Logistics System

The evolution of logistics management systems has been largely driven by advancements in Artificial Intelligence (AI), Internet of Things (IoT), and cloud computing, enabling the transformation from traditional, static supply chain models to dynamic, data-driven decision-making systems. NW Logistics represents a next-generation AI-powered logistics solution, designed to enhance operational efficiency, optimize transportation networks, reduce environmental impact, and improve safety compliance.

At its core, NW Logistics is built upon a multi-layered AI-driven framework, incorporating real-time monitoring, predictive analytics, and automated decision support. Unlike conventional logistics systems that depend on historical data and static route planning, NW Logistics continuously integrates real-time data streams from IoT devices, telematics, and geospatial intelligence, enabling proactive optimization of logistics operations.

This section outlines the architectural and functional principles of NW Logistics Fig. 2, detailing its data acquisition mechanisms, analytical models, and decision-support capabilities.

*1) Data acquisition and smart sensor integration:* A fundamental aspect of NW Logistics is its data acquisition framework, which relies on a network of smart sensors, embedded computing units, and mobile communication devices to ensure continuous data capture and real-time analytics processing. The system integrates high-precision telematics, including onboard cameras, GPS sensors, fuel efficiency trackers, and real-time cargo monitoring tools. The onboard cameras and computer vision modules analyze driver behavior, detect traffic violations, and assess road conditions to enhance safety compliance. GPS and GNSS sensors enable geospatial tracking with sub-meter accuracy, utilizing AI-powered route prediction models to suggest optimal delivery paths by considering traffic congestion, weather conditions, and road restrictions. Fuel efficiency sensors monitor fuel consumption patterns, assisting in $CO_2$ emissions tracking and reporting, ensuring alignment with

TABLE I. COMPARATIVE ANALYSIS OF AI METHODOLOGIES IN LOGISTICS APPLICATIONS

| Application | AI Methodology | Key Techniques | Computational Approach | IEEE Citation |
|---|---|---|---|---|
| **Explainable AI (XAI) for Logistics Decision-Making** | Explainable AI (XAI) | Decision Trees, SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations) | AI-driven decision support for logistics forecasting and inventory management | Oztekin et al., 2024 [12] |
| **AI-Driven Lithological Mapping for Logistics Optimization** | Machine Learning & Geospatial AI | Neural Networks, GIS-Based AI, Random Forests | Terrain-aware route optimization using AI-driven geospatial analysis | Morgan et al., 2024 [13] |
| **AI-Based Anomaly Detection for Supply Chain Risk Mitigation** | Supervised & Unsupervised Learning | Deep Learning, Clustering Techniques, Support Vector Machines (SVM) | AI-based fraud detection and supply chain risk assessment | Cartocci et al., 2024 [14] |

TABLE II. FUNCTIONAL CAPABILITIES AND REAL-WORLD APPLICATIONS OF AI-DRIVEN LOGISTICS SOLUTIONS

| Application | Primary Function | Real-World Use Case | IEEE Citation |
|---|---|---|---|
| **Explainable AI (XAI) for Logistics Decision-Making** | AI decision interpretability | Enhancing logistics forecasting, demand prediction, and inventory management | Oztekin et al., 2024 [12] |
| **AI-Driven Lithological Mapping for Logistics Optimization** | AI-powered terrain analysis | Optimizing transportation routes in complex environments (e.g., mountainous regions, industrial zones) | Morgan et al., 2024 [13] |
| **AI-Based Anomaly Detection for Supply Chain Risk Mitigation** | Risk mitigation and fraud detection | Identifying operational inefficiencies, fraudulent transactions, and logistical disruptions | Cartocci et al., 2024 [14] |

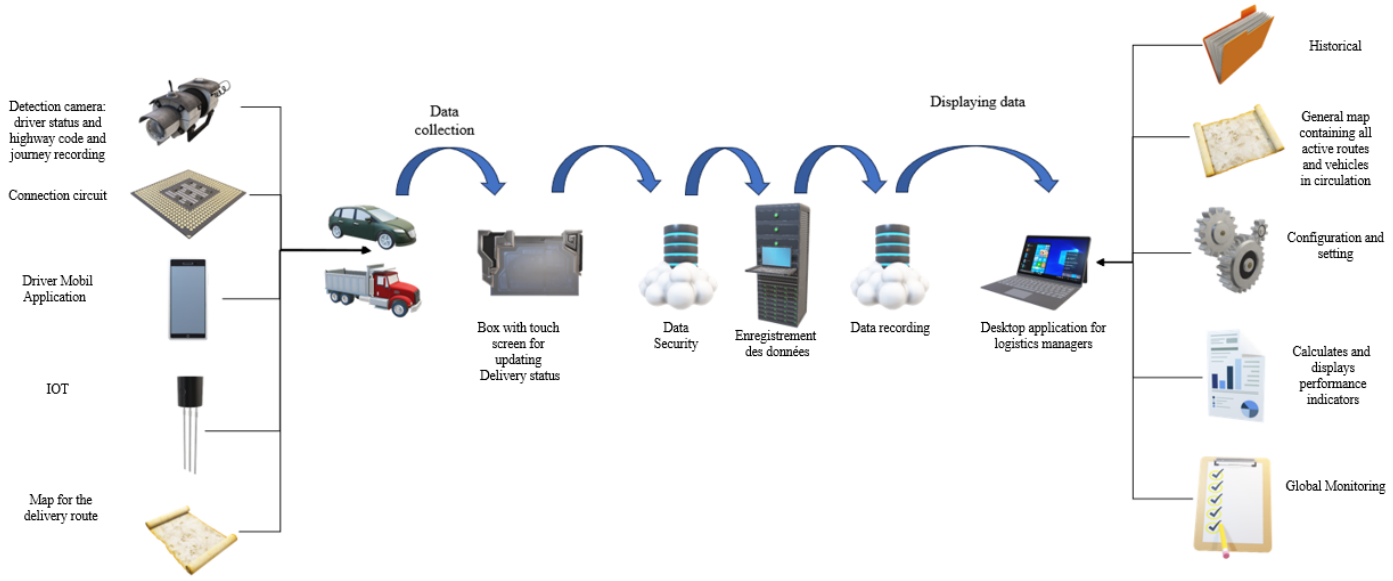


Fig. 2. The Architecture of NW logistics.

green logistics regulations. Additionally, real-time load and freight monitoring sensors enhance cargo security by detecting unauthorized access, temperature deviations, or weight fluctuations, while AI-driven demand forecasting optimizes loading and unloading schedules. Through this multi-modal sensor integration, NW Logistics establishes a real-time situational awareness model, significantly improving logistics decision-making and operational efficiency.

### *E. AI-Driven Analytics and Data Processing*

To effectively process and analyze vast amounts of real-time logistics data, NW Logistics employs a hybrid AI-driven computational framework, integrating edge computing, cloud-based storage, and high-performance machine learning algorithms. Data from onboard sensors and IoT devices is processed at the edge, allowing for low-latency analytics and immediate anomaly detection, which ensures proactive intervention in case of safety violations. Cloud storage serves as a centralized repository, aggregating multi-source logistics data to facilitate real-time analytics and historical trend analysis, while also ensuring scalability and secure data sharing across logistics networks.

The system's machine learning models optimize logistics operations through dynamic route planning, anomaly detection, and predictive analytics. Reinforcement learning algorithms dynamically adjust delivery routes based on real-time traffic conditions, road hazards, and delivery constraints, ensuring optimal efficiency and cost reduction. AI-driven driver behavior analysis employs computer vision and sensor data to monitor speed variations, fatigue detection through facial expression recognition, and risky driving behaviors such as sudden braking or lane deviations. Deep learning-based anomaly detection enhances fraud prevention, unauthorized vehicle use monitoring, and cargo security tracking, making NW Logistics a proactive risk management tool for logistics operators.

### F. User Interface and Logistics Control Center

NW Logistics provides an intuitive, AI-enhanced dashboard, allowing logistics managers and decision-makers to oversee fleet operations, analyze performance metrics, and optimize logistics processes in real time. The centralized logistics control panel displays live GPS locations, vehicle statuses, and estimated arrival times, ensuring full visibility into fleet operations. AI-powered predictive alerts notify managers of potential logistics disruptions before they occur, facilitating proactive decision-making and reducing downtime. Operational heatmaps provide geospatial visualization of traffic congestion, delivery bottlenecks, and fuel consumption trends, enabling data-driven optimization of supply chain logistics. In addition to real-time monitoring, NW Logistics incorporates automated compliance and sustainability reporting. A carbon emissions monitoring dashboard tracks $CO_2$ emissions per trip, ensuring compliance with green logistics standards and environmental regulations. Regulatory compliance alerts flag noncompliant driver behaviors, unauthorized route deviations, and safety violations, helping logistics companies adhere to industry regulations. AI-powered resource allocation and load balancing further optimize vehicle assignment and logistics planning, ensuring efficient use of transportation assets.

### G. NW Logistics as an Integrated AI Ecosystem

NW Logistics is more than just a logistics tracking system—it is a comprehensive AI-powered logistics ecosystem that integrates real-time AI processing, sustainability tracking, and fleet optimization into a single, intelligent platform. The system adapts dynamically to transportation conditions and logistics demands, leveraging AI-driven automation and predictive insights to enhance supply chain efficiency. By embedding carbon footprint tracking and fuel efficiency monitoring, NW Logistics supports environmentally responsible logistics operations, ensuring compliance with green logistics policies.

A key innovation of NW Logistics is its AI-based driver behavior analysis and fleet optimization capabilities. Using computer vision and sensor analytics, the system monitors driver performance, detects unsafe behaviors, and enhances road safety compliance. Through AI-powered predictive maintenance, NW Logistics minimizes vehicle downtime and maintenance costs, further optimizing supply chain resilience.

## V. Discussion

As Artificial Intelligence (AI) continues to redefine logistics and supply chain management [15], the need for multifunctional AI-driven logistics systems has become increasingly evident. Companies are striving to improve efficiency, sustainability, and security while optimizing their transportation networks to meet the growing demands of global trade and environmental regulations. NW Logistics represents an advanced, integrated AI-powered logistics system, incorporating real-time data processing, predictive analytics, carbon footprint monitoring, and AI-driven decision-making into a unified logistics framework [26].

While the three selected AI-driven logistics applications—Explainable AI (XAI) for decision support, Lithological Mapping for route optimization, and AI-based anomaly detection for risk mitigation—each contribute valuable advancements to logistics optimization, they remain domain-specific solutions, each addressing a singular aspect of logistics intelligence [14]. In contrast, NW Logistics stands out by synthesizing these AI functionalities into a single, adaptable, and intelligent logistics management system.

To provide a clearer understanding of NW Logistics' unique positioning, the following sections will explore the key similarities it shares with these existing AI applications, as well as the major differentiators that establish NW Logistics as a next-generation AI solution in the logistics industry.

### A. Similarities Between NW Logistics and AI-Driven Logistics Applications

Despite being a comprehensive and multi-functional AI system, NW Logistics shares several methodological and functional similarities with the selected applications. These parallels can be observed in three major areas:

*1) Predictive analytics and AI-Driven decision support:* Much like Explainable AI (XAI) models, NW Logistics integrates predictive analytics mechanisms to enhance supply chain forecasting and decision-making [27]. Through advanced AI-based forecasting models, NW Logistics empowers logistics operations by:

*a) Demand prediction:* Anticipating future logistics requirements and enabling supply chains to adjust proactively to market fluctuations.

*b) Inventory optimization:* Reducing storage costs and improving stock availability through AI-driven inventory control.

*c) Adaptive logistics planning:* Allowing for real-time adjustments to transportation schedules based on emerging road conditions, demand shifts, and operational constraints.

Unlike traditional AI models that function as black-box systems, NW Logistics emphasizes interpretability and transparency, ensuring that logistics managers understand and trust AI-driven recommendations. This approach not only enhances decision-making efficiency but also ensures compliance with industry regulations and corporate governance standards [16].

*2) AI-Powered route optimization:* NW Logistics shares strong methodological alignment with Lithological Mapping AI models, as both rely on machine learning algorithms to dynamically optimize transportation routes. These models leverage:

*a) Geospatial AI:* Analyzing topographical and environmental constraints to determine the most efficient transport routes while mitigating logistical bottlenecks.

*b) Dynamic routing algorithms:* Adjusting transport networks in real-time based on traffic congestion, weather patterns, and terrain complexities.

NW Logistics enhances this capability by integrating real-time IoT sensor data from its fleet, enabling the system to continuously adapt to evolving road conditions [20], [17]. This results in a highly responsive logistics system, capable of reducing delivery times, fuel costs, and overall transportation inefficiencies.

*3) Fraud detection and risk mitigation:* Similar to AI-based Anomaly Detection models, NW Logistics incorporates advanced machine learning techniques to improve logistics security and fraud prevention [14]. This includes:

*a) Real-Time monitoring of cargo and vehicle movements:* Identifying irregular transportation patterns to prevent unauthorized access or logistical inconsistencies.

*b) Detection of fraudulent activities:* Recognizing unauthorized route deviations, shipment tampering, and fuel misuse using AI-driven pattern recognition.

*c) Machine learning-based risk assessment:* Ensuring compliance with supply chain security regulations while proactively identifying operational vulnerabilities.

By integrating real-time AI monitoring with predictive risk analysis, NW Logistics offers a highly secure logistics network, reducing the likelihood of supply chain disruptions, financial fraud, and regulatory violations.

### B. Key Differentiators of NW Logistics

While NW Logistics shares functional similarities with existing AI-driven logistics applications, its comprehensive AI integration and real-time adaptability set it apart as a next-generation logistics management platform. NW Logistics outperforms these models by combining multiple AI-driven capabilities into a single, autonomous logistics ecosystem. Its key differentiators include:

*1) Real-Time AI integration for autonomous logistics operations:* Unlike traditional AI applications that rely heavily on historical data analysis, NW Logistics is designed as a real-time AI-powered logistics system. This allows for:

*a) Continuous AI-driven route optimization:* The system dynamically adjusts transport routes in real-time based on live traffic updates, weather conditions, and operational constraints [21].

*b) Live supply chain monitoring:* AI-powered monitoring enables proactive problem resolution, minimizing unexpected delays and logistical inefficiencies[22].

*c) Seamless data fusion from multiple sources:* By integrating GPS tracking, IoT-enabled sensors, and road infrastructure analytics, NW Logistics establishes a fully adaptive logistics ecosystem that can react instantaneously to environmental and operational changes[23][24].

This real-time AI integration ensures that NW Logistics functions as a self-optimizing logistics system, far exceeding the capabilities of static AI models that depend on periodic data updates.

*2) AI-Enabled sustainability and carbon emissions reduction:* A defining feature of NW Logistics is its AI-driven sustainability tracking system, a functionality absent in the selected AI applications. NW Logistics is uniquely designed to:

- Minimize Fuel Consumption and $CO_2$ Emissions through AI-powered route selection and eco-friendly driving recommendations [18].
- Enhance Fleet Efficiency by monitoring vehicle performance, driver habits, and logistics network sustainability metrics.
- Ensure Compliance with Green Logistics Regulations, enabling companies to align with carbon neutrality goals and environmental sustainability policies [19], [27],[28].

By incorporating real-time emissions tracking and fuel efficiency optimization, NW Logistics pioneers green logistics initiatives, providing companies with data-driven strategies to reduce their carbon footprint while maintaining cost efficiency.

*3) AI-Based driver behavior monitoring and road safety compliance:* NW Logistics integrates computer vision and AI-powered behavioral analysis to assess driver performance and safety compliance, a feature not present in the selected AI models. This system:

- Monitors Driver Behavior using AI-enhanced vehicle sensors and onboard cameras, detecting risky driving patterns such as speeding, abrupt braking, and lane violations [25].
- Detects Fatigue and Distraction through real-time facial recognition and biometric analysis, improving driver safety and reducing accident risks.
- Provides Automated Feedback and Training Recommendations, enabling fleet operators to implement AI-assisted driver training programs to enhance overall fleet safety.

This AI-driven approach not only improves road safety and fleet reliability but also contributes to lowering accident-related costs and optimizing vehicle longevity.

### C. Scientific Analysis of NW Logistics' AI Capabilities

The radar chart visualization highlights NW Logistics as a comprehensive AI-driven logistics solution, surpassing existing AI applications by integrating real-time decision-making, sustainability monitoring, and AI-enhanced security into a single platform Fig. 3.

NW Logistics excels in real-time AI integration, unlike XAI-based models that rely on historical data. It also shares route optimization capabilities with Lithological Mapping AI but advances further by incorporating IoT-driven dynamic routing and fuel efficiency tracking. Its predictive analytics align with XAI but extend to inventory forecasting and adaptive logistics planning.

In fraud detection and risk mitigation, NW Logistics mirrors Anomaly Detection AI but enhances security with real-time monitoring of cargo movements, route deviations, and unauthorized vehicle use. Additionally, its AI-powered sustainability tracking is unique, reducing $CO_2$ emissions and optimizing fuel consumption, a feature missing in other models.

A key differentiator is its driver behavior analysis, employing computer vision to detect risky driving, fatigue, and compliance violations, ensuring road safety and fleet optimization [30], [29].

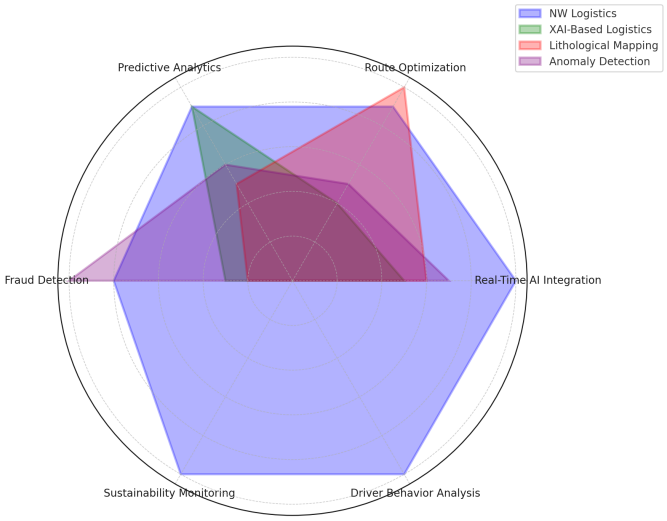


Fig. 3. The Radar chart visualization.

NW Logistics stands out as a next-generation AI-powered logistics platform, integrating real-time optimization, security, and environmental sustainability in a unified system, redefining modern supply chain intelligence.

## VI. Conclusion

The integration of Artificial Intelligence (AI), Internet of Things (IoT), and cloud computing has significantly accelerated the digital transformation of logistics. NW Logistics is a next-generation AI-powered logistics platform that integrates real-time monitoring, predictive analytics, dynamic route optimization, fraud detection, and environmental impact assessment. Its multifunctional AI-driven approach allows logistics networks to become more adaptive, efficient, and environmentally responsible, in line with global industry trends and sustainability objectives.

Using AI and IoT based solutions, NW Logistics improves decision making and operational efficiency while supporting low-carbon logistics planning. Through energy-efficient route management and real-time fuel optimization, the platform enables smarter and greener logistics operations. It also integrates AI-enhanced fleet management, driver behavior tracking, and CO2 emissions monitoring to ensure compliance with green logistics standards.

Incorporating disruptive technologies such as smart sensors, crowd-shipping, and drone-based logistics, NW Logistics addresses the challenges of last-mile delivery and promotes circular economy principles. Its modular design supports adaptability across intermodal transport networks and facilitates real-time logistics intelligence.

Looking ahead, future developments of NW Logistics will focus on the integration of advanced computer vision and deep learning models for the detection of all types of road signs, traffic regulations, and driving violations. This enhancement aims to create a fully intelligent driving monitoring system that contributes to improved safety and compliance across logistics fleets. In parallel, the platform will evolve to offer a more robust enterprise logistics tracking system, capable of monitoring key performance indicators, managing delivery chains in real time, and providing detailed behavioral reports for drivers and operators.

As logistics and supply chain networks continue to evolve in complexity, NW Logistics positions itself as a scalable, intelligent, and responsible solution that bridges operational performance, regulatory compliance, and environmental sustainability. Through ongoing innovation and applied AI, the platform will continue to transform logistics into a safer, smarter, and greener industry.

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# A Robust Defense Mechanism Against Adversarial Attacks in Maritime Autonomous Ship Using GMVAE+RL

Ganesh Ingle, Kailas Patil, Sanjesh Pawale
Department of Computer Engineering, Vishwakarma University, Pune, India

***Abstract*—In this paper, we propose a robust defense framework combining Gaussian Mixture Variational Autoencoders (GMVAE) with Reinforcement Learning (RL) to counter adversarial attacks in Maritime Autonomous Systems, specifically targeting the Singapore Maritime Database. By modeling complex maritime data distributions through GMVAE and dynamically adapting decision boundaries via RL, our approach establishes a resilient latent representation space that effectively identifies and mitigates adversarial perturbations. Experimental evaluations using adversarial methods such as FGSM, IFGSM, DeepFool, and Carlini-Wagner attacks demonstrate that the proposed GMVAE+RL model outperforms traditional defenses in both accuracy and robustness. Specifically, it achieves a peak accuracy of 87% and robustness of 20.5%, compared to 85.8% and 19.2% for FGSM and significantly lower values for other methods. These results underscore the superiority of our method in ensuring data integrity and operational reliability within complex maritime environments facing evolving cyber threats.**

***Keywords*—Maritime autonomous systems; reinforcement learning; defense mechanisms; Gaussian Mixture Variational Auto encoder; Singapore maritime database**

## I. Introduction

The maritime industry is experiencing a paradigm shift with the advent of Artificial Intelligence (AI), which is set to revolutionize various operational facets through heightened automation, efficiency enhancement, and cost mitigation.

### A. Maritime Autonomous Systems (MAS)

AI's instrumental role is exemplified in the development of Maritime Autonomous Systems (MAS), which necessitate minimal human governance, employing AI for executive decisions and navigational control [1],[2],[5].

### B. Advantages of MAS

MAS herald a new era in maritime operations, characterized by:

- Diminished manpower requisites, leading to significant labor cost reductions.
- AI-facilitated automation and refinement of complex maritime tasks.
- Augmented crew safety, especially under perilous operational conditions.
- Operational cost economization through heightened MAS efficiency.
- Environmental impact mitigation via the integration of renewable energy sources.

### C. MAS Development Progress

Rapid advancements in MAS development are being witnessed, with a multitude of applications ranging from cargo transit to environmental oversight.

### D. Security Implications of AI in MAS

However, the ascent of AI within MAS introduces new security paradigms, predominantly concerning Adversarial Artificial Intelligence (AAI).

### E. Adversarial Artificial Intelligence (AAI)

AAI encapsulates the intentional manipulation of AI frameworks, aiming to pinpoint and capitalize on systemic vulnerabilities, thus posing a significant threat to MAS security and operational integrity.

### F. AAI Vulnerabilities in MAS

MAS AI systems are susceptible to various AAI attacks due to their reliance on complex algorithms and data-driven decision-making processes. Manipulating training data to introduce biases or errors in the AI model, leading to incorrect decisions or system malfunctions. Model inversion: Inferring sensitive information from the AI model's parameters, such as training data or model architecture.Crafting inputs that the AI model misclassifies or misinterprets, potentially enabling attackers to evade detection or manipulate system behavior [35],[36]. Inference attacks: Exploiting the AI model's decision-making process to influence its outputs, such as steering a vessel towards a hazardous area or triggering false alarms [3], [4], [6]. Impact of AAI on MAS Security Collisions: Attackers could manipulate the AI navigation system to cause collisions with other vessels or obstacles, leading to loss of life and environmental damage. Cargo theft: Attackers could intercept or reroute cargo shipments, causing financial losses and disrupting supply chains. Attackers could exploit vulnerabilities in the AI system to gain unauthorized access to sensitive data or disrupt critical operations. The rapid advancements in artificial intelligence (AI) have opened up a plethora of opportunities for enhancing maritime operations through autonomous systems. However, the integration of AI into maritime autonomous systems (MAS) also introduces new security challenges, particularly from adversarial AI (AAI).

AAI refers to the malicious use of AI to exploit vulnerabilities and compromise the integrity of AI-powered systems. The infusion of AI into maritime operations has catalyzed a transformative phase in the maritime sector, yet it simultaneously ushers in new security vulnerabilities, especially from AAI.

### G. AAI Threats in the Maritime Domain

The maritime sector's intrinsic dynamic and unpredictable nature exacerbates the vulnerability of AI systems to AAI threats. These threats encompass:

### H. Data Poisoning

Adversarial entities may corrupt training datasets, inducing biases or errors that could precipitate erroneous decision-making or functional disruptions within MAS.

### I. Model Inversion

Attackers might extract sensitive data or discern the model's structure from its parameters, thus acquiring tactical knowledge about the system's operations.

### J. Evasion Attacks

Specially crafted inputs may lead AI models to misclassify or misconstrue data, permitting adversaries to skirt detection or alter system actions.

### K. Inference Attacks

Exploitation of the decision-making process within AI models can be manipulated to influence outcomes, potentially resulting in navigational errors or security breaches.

The maritime industry is undergoing a transformative evolution with the integration of Artificial Intelligence (AI) into Maritime Autonomous Systems (MAS), promising enhanced operational efficiency, reduced human intervention, and improved safety. MAS rely heavily on AI-driven decision-making for navigation, cargo management, and environmental monitoring. However, as the reliance on AI systems deepens, so does the surface for security vulnerabilities—particularly from Adversarial Artificial Intelligence (AAI), which involves deliberate perturbations in input data that can mislead AI models into making erroneous or even dangerous decisions [6-14].

Previous studies have investigated adversarial attacks and their countermeasures, primarily in controlled or theoretical environments using static defense mechanisms such as adversarial training, input transformations, or model distillation. While these approaches show promise in generic settings, they often fall short in real-world maritime environments characterized by high data variability, dynamic vessel behaviors, and critical security requirements. Specifically, existing defense strategies lack adaptability and robustness when confronted with iterative, optimization-based attacks like Carlini-Wagner or DeepFool, which can subtly and effectively compromise AI models without detection.

This presents a significant research gap: there is a pressing need for defense mechanisms that can not only model complex, multimodal maritime data distributions but also dynamically adapt to evolving attack strategies in real time. Addressing this, we propose a hybrid defense architecture that combines Gaussian Mixture Variational Autoencoders (GMVAE) for resilient data representation with Reinforcement Learning (RL) for adaptive policy optimization. The GMVAE component ensures a structured latent space capable of identifying subtle anomalies, while RL empowers the model to learn countermeasures through continuous feedback, improving robustness over time.

By focusing on the underexplored intersection of generative modeling and adaptive learning in adversarial defense, this research provides a practical and scalable solution tailored to the maritime domain. The approach is validated on the Singapore Maritime Dataset, demonstrating superior performance over existing methods in terms of both accuracy and adversarial robustness. This work not only fills a critical gap in maritime cybersecurity literature but also sets a foundation for future research in real-time, adaptive AI defense systems.

Compared to traditional defense strategies such as adversarial training, input transformation, and static regularization techniques, the proposed GMVAE+RL framework offers multiple significant advantages. Firstly, the GMVAE component excels at capturing multi-modal and complex maritime data distributions, enabling it to identify subtle perturbations that static defenses often miss. Secondly, the integration of Reinforcement Learning provides an adaptive mechanism that dynamically adjusts the model's behavior in response to evolving attack strategies—something existing models lack. Thirdly, the hybrid approach enhances both generalization and interpretability by learning structured latent representations and optimizing decision policies simultaneously. Experimental comparisons against established methods like FGSM, IFGSM, DeepFool, and Carlini-Wagner reveal that our method maintains higher accuracy and robustness, with a notable 87% accuracy and 20.5% robustness even under strong adversarial conditions. These outcomes underscore the model's superior resilience and adaptability, making it highly suitable for real-world applications in autonomous maritime systems where data integrity and security are mission-critical.

The remainder of this paper is organized as follows: Section II provides the background and motivation for adversarial resilience in Maritime Autonomous Systems, followed by a review of related work in Section III. Section IV details the proposed methodology combining GMVAE and Reinforcement Learning, while Section V outlines the experimental setup used for evaluation. Section VI presents a comprehensive analysis of results, including performance metrics under various adversarial scenarios. Finally, Section VII concludes the paper with key findings and directions for future research.

## II. Background

Global trade heavily relies on maritime vessels, with a significant portion of international movement facilitated by shipping [5]. This paper explores the integration of advanced sensors in fully autonomous vessels (Level 4 as defined by the International Maritime Organization), which operate independently without any human crew.

MAS utilize a variety of sensors and instruments for environmental perception and decision-making, including:

- RADAR: For detecting large objects using radio waves.
- LiDAR: Employed for accurate detection of smaller objects.
- Echo Sounders: Utilized for underwater object detection.
- CCTV/IR/multispectral Cameras: For close-range object detection.
- Microphone Arrays: Capture audio cues for situational awareness.
- AIS and GNSS: Provide location and data transmission capabilities.
- ECDIS, Weather Sensors, and Communication Systems: Crucial for navigation and environmental monitoring.
- Specialized sensors and Drones: Extend the range and capabilities of standard sensor systems.

The integration of multiple sensors provides increased accuracy, improved redundancy, and enhanced situational awareness. Sensors in MAS face unique challenges such as water-induced distortions, harsh environmental conditions, and detection complexities. The effective deployment of a diverse sensor array is paramount in MAS, requiring a deep understanding of their individual and collective capabilities and limitations in the maritime context. In fully autonomous maritime systems, AI plays a crucial role in automating vessel operation. It receives sensor data as input, analyzes the information, and makes decisions to control the vessel's actions, replacing or supplementing crew functions. The specific AI technologies required depend on the range of tasks and functionalities of the MAS. Based on the categorization, several key AI technologies are employed in MAS, connected to a Dynamic Positioning (DP) system that controls the vessel's movements:

Determines the vessel's real-time location and environment, including object detection and range. Convolutional neural networks (CNNs), region proposal networks(RPNs), and natural language processing (NLP) for interpreting communication.Sensor data, including camera images, radar signals, and LiDAR data.Real-time information about the vessel's surroundings and potential hazards. Prevents collisions with other vessels or objects [14-23]. CNNs for object recognition and support vector machines (SVMs) for trajectory planning.SA information, including object detection data.New trajectory to avoid collisions.Determines the optimal route for the vessel, considering factors like fuel efficiency, speed, and safety.Evolutionary algorithms (EAs), particle swarm optimization (PSO), and ant colony optimization (ACO).Global map data, weather information, and vessel parameters.Optimal route for the vessel to follow.

- Convolutional Neural Networks (CNNs): Efficiently learn spatial features from images, making them ideal for object detection and recognition in SA and collision avoidance modules.
- Region Proposal Networks (RPNs): Generate candidate object bounding boxes within images, improving the efficiency of object detection for SA.
- Natural Language Processing (NLP): Enables interpretation of communication signals like radio messages, enhancing situational awareness.
- Support Vector Machines (SVMs): Effective for classification tasks, such as determining the type of object detected and generating new collision-avoidance trajectories.
- Evolutionary Algorithms (EAs): Powerful optimization techniques that can handle complex multi-objective problems, like finding the optimal global route for the vessel.
- Particle Swarm Optimization (PSO): Mimics the behavior of a swarm of birds to find optimal solutions, applicable to path planning and route optimization.
- Ant Colony Optimization (ACO): Inspired by the foraging behavior of ants, ACO can identify efficient routes by simulating pheromone communication. AI plays a pivotal role in automating various aspects of MAS operation. Different AI technologies are employed for specific tasks, from situational awareness and collision avoidance to global path planning and vessel maintenance. Understanding the capabilities and limitations of these AI technologies is crucial for designing and developing safe and reliable MAS.

Most evaluations of adversarial attacks on machine learning (ML) systems have been limited to controlled laboratory environments. This study extends the analysis to real-world MAS environments, where the implications of such attacks are less understood but potentially more impactful.

While focusing on adversarial attacks, this work also acknowledges the significance of conventional cybersecurity attacks and the potential for combined adversarial AI and conventional cybersecurity tactics. The influence of conventional security vulnerabilities on both AI-based and traditional security is also recognized.

### A. Class 1: Model Inversion

- Description: An attacker queries the ML model to deduce its prerequisite features, potentially aiding in reconnaissance for future attacks.
- Impact: This represents an abuse of the system's confidentiality, although it does not directly impair the model's functionality.

This comprehensive evaluation of adversarial attacks in MAS provides critical insights into their real-world implications, emphasizing the need for robust defense mechanisms in maritime autonomous systems.

## III. Literature Survey

Huang et al. represents a critical juncture in the field of artificial intelligence, particularly in understanding the vulnerabilities of reinforcement learning (RL) systems to adversarial attacks. Reinforcement learning, which functions on a framework of rewards and penalties, had been increasingly applied in varied domains such as gaming, autonomous navigation, and decision-making algorithms. However, the robustness of

these systems against subtle, malicious alterations had not been thoroughly examined until this study.This research focused on the concept of adversarial attacks, previously acknowledged in other neural network contexts, where slight, calculated changes to input data could drastically mislead the network's output. They applied this concept to RL, investigating whether minor perturbations in the input data of an RL agent could derail its performance. Their experiments cut across different RL environments to ensure a comprehensive assessment.The findings were revelatory, demonstrating that even negligible modifications to input data could significantly impair the RL models' performance. This vulnerability was not confined to specific RL algorithms or tasks but was a more generalized issue, indicating a fundamental security risk in RL applications. Crucially, the study's implications extended beyond the immediate realm of RL, casting a spotlight on the need for adversarial robustness in AI systems, particularly in safety-critical applications like autonomous vehicles[23-29].Presented research precipitated a heightened awareness and subsequent research efforts aimed at developing more robust RL systems capable of resisting such adversarial attacks. The study not only emphasized the importance of considering security threats in AI system design but also spurred advancements in defensive techniques, marking a significant leap in the development of secure and reliable AI solutions.

Chen et al. provided a crucial insight into the cybersecurity vulnerabilities of Connected Vehicle (CV) based transportation systems, particularly focusing on the risks associated with data spoofing attacks. In the era of advanced transportation technology, CV systems have emerged as a key innovation, enhancing vehicular communication and operational efficiency through vehicle-to-vehicle and vehicle-to-infrastructure interactions. However, the integration of such complex communication systems also opens up new avenues for cyber threats.Proposed study embarked on a comprehensive analysis of the CV systems' architecture and operational mechanisms. Their primary objective was to identify and assess potential cybersecurity threats, with a special emphasis on data spoofing – a technique where false information is injected into a system, leading to misguided actions or responses. Through detailed simulations and hypothetical attack scenarios, the study highlighted how these systems are particularly prone to data spoofing, which could lead to severe consequences like traffic disruptions or even collisions [29],[30].

One of the key revelations of this study was the identification of inherent design flaws within CV systems that made them susceptible to such cyberattacks. These vulnerabilities could potentially be exploited to manipulate critical aspects of traffic control or to feed misleading information to vehicles, thus compromising road safety. The findings played a pivotal role in emphasizing the need for robust, multi-layered cybersecurity measures within CV systems. This study not only underscored the importance of incorporating stringent security protocols in the design and implementation of CV technology but also acted as a catalyst for further research and development in enhancing the resilience of connected vehicles against cyber threats. The work of Chen and colleagues thus marked a significant step in ensuring that the advancements in vehicle connectivity and automation do not compromise safety and security [31[32]. Lin et al. introduced a groundbreaking approach to adversarial attacks within the realm of Atari games, marking a significant advancement in the understanding of vulnerabilities in reinforcement learning systems. Their innovative concept, termed "strategically-timed attacks," involved the creation of adversarial examples that were calculated independently at each timestep of the game. This method diverged from traditional continuous attack models, offering a more nuanced and potentially more disruptive technique. By strategically timing these attacks, Lin and colleagues demonstrated that it was possible to significantly impair the performance of reinforcement learning agents in game scenarios. These attacks were designed to be subtle enough to avoid immediate detection, yet sufficiently impactful to mislead the agents, leading to incorrect decisions or actions within the game. This research not only highlighted a specific vulnerability in reinforcement learning applications but also set a new precedent in the methodology of adversarial attack strategies. It underscored the need for more robust defense mechanisms in AI systems, particularly in environments where decision-making is based on real-time data inputs, such as in gaming or autonomous navigation scenarios. The work of Lin et al. thus stands as a pivotal contribution to the field of AI security, illustrating the evolving nature of cyber threats and the ongoing challenge of securing AI against sophisticated adversarial techniques.

Xiang et al. conducted a noteworthy study focusing on the domain of Q-learning, specifically within the context of automatic path planning. Their research made a significant contribution to the field by proposing a probabilistic output model designed to predict adversarial examples in such structured environments. The essence of their work revolved around the exploration of adversarial attacks in scenarios that are inherently more systematic and organized, compared to the often chaotic nature of other environments like gaming.The innovative aspect of research lay in the application of their model to Q-learning, a fundamental reinforcement learning technique widely used for making sequence-based decisions. By integrating a probabilistic approach, they were able to forecast the likelihood of adversarial instances occurring in an automatic path planning context. This model was not only pivotal in identifying potential vulnerabilities within the path planning algorithms but also in suggesting the probability of certain attacks succeeding.Their work shed new light on the dynamics of adversarial attacks in environments characterized by a high degree of order and predictability, such as route planning and navigation. By doing so,authors expanded the understanding of how adversarial attacks could be tailored and predicted in such settings, contrasting with the more generalized approach typically seen in other AI applications. The implications of this study are far-reaching, especially considering the growing reliance on autonomous systems in various sectors, including transportation and logistics. It underscores the need for advanced security measures that can anticipate and mitigate such sophisticated cyber threats in automated and algorithm-driven environments.

Huang et al. not only exposed the vulnerabilities of reinforcement learning systems to adversarial attacks but also introduced a significant defensive mechanism known as the Fast Gradient Sign Method (FGSM). This method was designed specifically to counteract the negative impacts of adversarial inputs, especially in the context of deep reinforcement learning agents.FGSM operates by utilizing the gradients of

the neural network to create perturbations that 'push' the input data towards the direction of increasing the loss. This method is particularly notable for its simplicity and efficiency. Instead of requiring complex or time-consuming computations, FGSM generates adversarial examples by applying a straightforward adjustment in the direction of the gradient. The 'sign' component of the method refers to taking the sign of the gradient, ensuring that the perturbations are small yet effective enough to mislead the learning model.In the context of deep reinforcement learning, where agents are often trained on high-dimensional input data such as images or sensor readings, FGSM provides a valuable tool for enhancing the robustness of these systems. By applying adversarial examples generated via FGSM during the training process, the learning models can be 'inoculated' against potential attacks, learning to recognize and resist manipulative inputs. This approach essentially strengthens the model's ability to maintain performance even when faced with subtly altered input data, a critical requirement in applications where reliability and accuracy are paramount.Authors highlights the FGSM's role in defending against adversarial attacks has been pivotal in the field of AI security. It marked a step forward in developing more secure AI systems capable of operating reliably in adversarial environments, a vital consideration as AI technologies continue to be integrated into increasingly critical and sensitive applications.

Silver et al. applied RL to the game of Go. They introduced a novel approach that combined deep neural networks with tree search, leading to unprecedented performance in this complex board game. This demonstrated RL's potential in mastering highly intricate and strategic tasks. Mnih et al. were pioneers in applying deep learning to RL, particularly in the context of playing Atari games. Their model was the first to successfully learn control policies directly from high-dimensional sensory inputs, marking a significant advancement in the field of game-playing AI.

The increasing prevalence of deep learning applications has brought to light the vulnerability of these models to adversarial attacks. These attacks involve crafting subtle modifications to input data that can cause deep learning models to make erroneous predictions. Even minor perturbations can have a significant impact on model performance. This poses a serious threat to the reliability of deep learning systems, especially in critical applications such as autonomous vehicles and medical diagnosis.

The Fast Gradient Sign Method (FGSM) [1] is a fundamental adversarial attack technique that involves calculating the gradients of the model's loss relative to the input data and modifying the data based on these gradients. This method was expanded into IFGSM [2], which applies perturbations iteratively to increase the strength of the adversarial effect. More complex methods like the DeepFool attack [3] and the Carlini-Wagner attack [4] employ advanced strategies. DeepFool iteratively identifies the minimal perturbation needed to misclassify an input by approximating the decision boundary, whereas the Carlini-Wagner attack uses optimization techniques to create adversarial examples with minimal changes but targeted misclassification goals.

Various defense strategies have been proposed to mitigate adversarial threats. Adversarial training [5] involves training models using adversarial examples to enhance their robustness. Other techniques, like feature squeezing and input transformations (including JPEG compression) [6], aim to eliminate adversarial perturbations. However, these methods often struggle to generalize across different types of attacks, highlighting the need for more innovative solutions.

Variational Autoencoders (VAEs) [7] provide a structured framework for learning generative models. They consist of an encoder, which maps input data into a latent space, and a decoder, which reconstructs data from these latent representations. The learning objective is to minimize reconstruction loss while ensuring the latent space adheres to a structured distribution, typically using the Kullback-Leibler (KL) divergence. This latent space captures essential features for controlled data generation. Extending VAEs, Gaussian Mixture Variational Autoencoders (GMVAE) [8] incorporate Gaussian Mixture Models (GMMs) into the latent space, enabling the representation of complex, multi-modal data distributions, thereby overcoming some limitations of standard VAEs.

Reinforcement learning has been identified as a promising method for improving model resilience against adversarial attacks [9]. This approach applies principles from control theory, using a policy network that learns actions to maximize cumulative rewards. In defense contexts, these actions involve decisions that enhance model robustness. This method involves training the policy network to make decisions that lead to accurate predictions on adversarial examples, counteracting adversarial perturbations. The reinforcement learning framework offers the benefit of continual adaptation, allowing models to enhance their robustness over time.

The MNIST dataset [10] has been a benchmark in machine learning for testing various defense techniques, contributing significantly to our understanding of adversarial challenges and defense strategies. This research includes both traditional and advanced deep learning-based solutions aimed at protecting model performance under adversarial conditions.

Adversarial training and defensive distillation, two current defenses for CNN-LSTM models, have trouble being effective and generalizing against adversarial attacks in PQD classification. These techniques fall short of maintaining high precision when attacked, indicating a need for more flexible and effective defense tactics. This is addressed by Input Adversarial Training (IAT), which meets a crucial demand for CNN-LSTM model security in power system applications by improving model robustness while maintaining performance [32]. Current adversarial defenses frequently lack an ideal balance between accuracy and robustness. Feature masking's potential is still not fully realized, particularly when paired with gradient modification. As our study showed, this disparity emphasizes the need for effective measures that improve resilience without lowering performance [33].

Existing GNN defence methods focus on highly linked training processes, overlooking adaptive adversarial attack strategies. This study addresses the gap by introducing GNN Attacker, leveraging Energy Honey Badger Optimization (EHBO) for generating adversarial attacks. The model achieves high visual similarity 90.77%, classification accuracy 94.68%, and attack success rate 96.54%, demonstrating its effectiveness in testing GNN robustness [34].

Existing deep learning models are highly vulnerable to

adversarial attacks, which introduce subtle perturbations leading to misclassification. Detecting and mitigating these attacks remains a significant challenge. This review addresses the gap by providing a comprehensive analysis of adversarial attack strategies and defense mechanisms, contributing to the development of more resilient deep learning and machine learning models [35].

Existing research on adversarial robustness has explored various defense mechanisms, including adversarial training, input transformations, and feature denoising. However, optimizing bit plane slicing for resilience remains underexplored. This study leverages genetic algorithms to refine bit-depth configurations, revealing that 5-bit representations enhance robustness against FGSM and DeepFool attacks. Despite performance degradation under adversarial conditions, optimized models demonstrate significant recovery. Prior work lacks dynamic bit plane adaptation, evaluation on diverse attacks, and scalability to large datasets. Addressing these gaps through adaptive slicing, black-box evaluations, and hybrid defenses can further strengthen adversarial resilience [36] [37].

Despite progress in defending against adversarial attacks, a gap remains in developing robust, generalizable solutions. Current defenses often perform well against certain attack types but are less effective in varied adversarial scenarios. This study seeks to address this gap by combining the capabilities of GMVAEs and reinforcement learning. This innovative approach aims to harness the unsupervised feature learning of GMVAEs and the adaptability of reinforcement learning's policy optimization, proposing a new direction for enhancing defense mechanisms against adversarial threats.

Existing defense mechanisms against adversarial attacks in Maritime Autonomous Systems (MAS) largely focus on either static adversarial training or heuristic input transformations, which often lack adaptability and fail to generalize across evolving attack strategies. These approaches struggle particularly in complex, real-world maritime contexts such as the Singapore Maritime Database, where data is highly dynamic and multi-modal. To bridge this gap, we propose a novel hybrid defense framework that integrates Gaussian Mixture Variational Autoencoders (GMVAE) with Reinforcement Learning (RL) to create an adaptive, resilient latent space capable of detecting and mitigating sophisticated adversarial manipulations. The GMVAE component excels in modeling diverse data distributions and isolating irregular patterns, while RL dynamically adjusts model responses based on feedback from adversarial environments. Experimental evaluations using standard adversarial methods—FGSM, IFGSM, DeepFool, and Carlini-Wagner—reveal that our approach significantly outperforms conventional defenses, achieving an accuracy of 87% and robustness of 20.5%, compared to lower benchmarks from existing methods. By explicitly addressing the shortcomings of static defenses and introducing an adaptive learning mechanism, our work advances the state of the art in maritime cybersecurity, ensuring higher integrity and reliability of autonomous ship operations under adversarial conditions.

## IV. Methodology

Fig. 1 gives proposed architecture diagram for the GMVAE with reinforcement learning.

In the realm of machine learning, the Gaussian Mixture Variational Autoencoder (GMVAE) stands out for its proficiency in processing complex, multi-modal data distributions. This model excels due to its capacity to discern diverse data representations by employing a combination of Gaussian distributions within its latent space. This capability surpasses that of the traditional Variational Autoencoder (VAE). In the context of adversarial attacks, which are tactics used to subtly alter input data to mislead machine learning models into erroneous predictions or classifications, the stakes are high. These attacks could result in various detrimental outcomes, such as mislabeling of ships, inaccuracies in maritime tracking, or even jeopardizing port security.

In safeguarding the Singapore Maritime Database against such adversarial threats, the GMVAE emerges as a key tool. Its sophisticated approach to data representation makes it highly effective in enhancing the database's defense mechanisms against these types of cyber threats.

*1) Latent space modeling:* The GMVAE, a sophisticated machine learning model, structures data within its latent space as a blend of Gaussian distributions. Each Gaussian element, characterized by its mean $\mu_k$ and standard deviation $\sigma_k$, encapsulates a distinct aspect of the data's distribution.

*2) Enhanced pattern recognition:* GMVAE's advanced data interpretation allows it to discern intricate patterns and irregularities with greater precision than more basic models, making it a valuable asset in identifying subtle discrepancies.

*3) Handling data uncertainty:* The GMVAE's probabilistic approach is instrumental in gauging uncertainty. This feature is vital for pinpointing and understanding manipulated data points, commonly known as adversarial examples, within the Singapore Maritime Database. This capability is crucial in bolstering the database's defenses against adversarial cyber attacks.

Defending against adversarial attacks on the Singapore Maritime Database, the Gaussian Mixture Variational Autoencoder (GMVAE) plays a crucial role with its encoder network, latent space representation, and decoder network. Each component of the GMVAE contributes to enhancing the robustness of the system against such attacks:

The encoder in a GMVAE takes an input vector $x$ (representing maritime data) and maps it to the parameters of a Gaussian mixture model in the latent space. Mathematically, this can be expressed as a function

$$f : x \to (\mu_k, \sigma_k^2) \tag{1}$$

where $\mu_k$ and $\sigma_k^2$ are the mean and variance of the $k$-th Gaussian component in the latent space. This encoding process translates complex, high-dimensional maritime data into a structured latent space. By doing so, it aids in differentiating standard operational data from potentially manipulated (adversarial) inputs. The encoder's effectiveness in this mapping is crucial for early detection of data inconsistencies or anomalies that could indicate a security breach. In the latent space, data points are represented as a mixture of Gaussian distributions. This can be mathematically formulated as

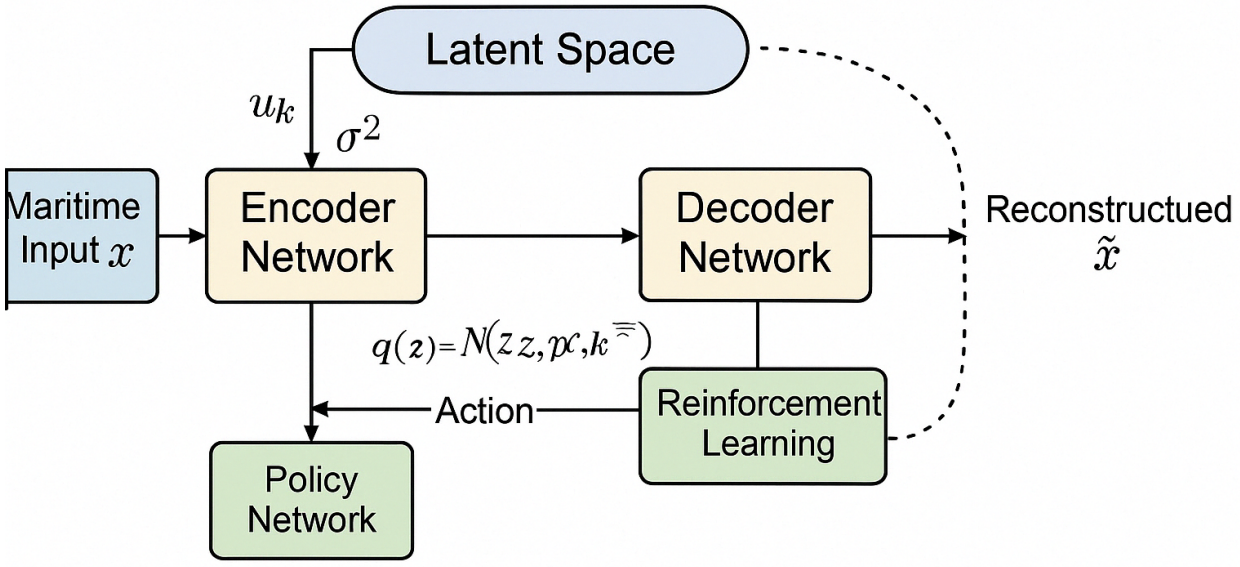


Fig. 1. Architecture diagram for proposed method.

$$p(z) = \sum_{k=1}^{K} \pi_k \mathcal{N}(z; \mu_k, \sigma_k^2) \tag{2}$$

where $z$ is the latent variable, $\pi_k$ is the mixture coefficient for the $k$-th component, and $\mathcal{N}$ denotes the Gaussian distribution. The latent space's ability to model complex data distributions enables the identification of subtle deviations from typical data patterns. This is particularly useful in the maritime context for detecting adversarial manipulations like forged vessel locations or tampered cargo records. The probabilistic nature of this space allows for a more nuanced understanding of data uncertainty, which is key in identifying adversarial examples.

The decoder network aims to reconstruct the input data from its latent representation. This can be viewed as a function:

$$g : (\mu_k, \sigma_k^2) \to \hat{x} \tag{3}$$

where $\hat{x}$ is the reconstructed input. The decoder's role in defense is to reconstruct the input data from the latent representation and compare it with the actual input. Significant deviations in this reconstruction process can indicate adversarial manipulations. Mathematically, if the reconstruction loss, typically measured as the difference between $x$ and $\hat{x}$ (e.g., using mean squared error), exceeds a certain threshold, it may signal an anomaly. The GMVAE's encoder network mathematically transforms maritime data into a structured latent space, where data points are probabilistically modeled as a mixture of Gaussians. This transformation is key to detecting abnormalities in the data, which could signify adversarial attacks. The latent space serves as a critical junction for identifying unusual data distributions that diverge from standard patterns. Finally, the decoder's mathematical reconstruction of the input data provides a means to verify the integrity of the data, making it a vital component in the detection and defense against adversarial threats in the Singapore Maritime Database.

- Anomaly Identification: Utilizing its advanced capabilities, the GMVAE can pinpoint irregularities in standard data patterns, which could indicate adversarial interference. This feature is particularly valuable in spotting potential cyber threats within the maritime data.
- Data Integrity Checks: The process of reconstructing input data from its latent representation in GMVAE serves as a critical check. Any significant mismatches between the original and reconstructed data are red flags that may denote a cyber intrusion.
- Dynamic Adaptation: Continuously integrating new data into the GMVAE enables it to stay abreast of changing adversarial techniques, enhancing its ability to safeguard against evolving cyber threats.

Embedding the GMVAE within the cybersecurity framework of Singapore's maritime database equips it with a sophisticated mechanism to detect and counter adversarial attacks. The model's proficiency in managing complex data and its adeptness at modeling uncertainty render it a powerful asset in defending against such sophisticated cyber challenges.

In the application of the Gaussian Mixture Variational Autoencoder (GMVAE) for defending the Singapore Maritime Database against adversarial cyber attacks, the encoder's output representation $q(z|x)$ plays a crucial role, defined mathematically as:

$$q(z \mid x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(z \mid \mu_k(x), \sigma_k^2(x)) \tag{4}$$

This formulation encompasses several key components: $K$ represents the number of Gaussian components in the mixture,

critical for modeling complex maritime data patterns; $\pi_k$ is the mixing coefficient for the $k$-th component, reflecting its relative significance in the mixture; and $\mathcal{N}(z|\mu_k(x), \sigma_k^2(x))$ denotes the Gaussian distribution for each component, conditioned on the input $x$. These components collectively enable the GMVAE to perform a detailed and probabilistic mapping of input data to the latent space, which is essential for detecting deviations from normal data behavior that might indicate adversarial activities. Through such sophisticated mathematical modeling, GMVAE significantly enhances the capability to identify and mitigate potential cyber threats in the maritime database.

- Complex Data Modeling with Gaussian Mixtures: GMVAE's ability to represent intricate data distributions as a mixture of Gaussian components is crucial. This enables the detection of nuanced patterns and variations in maritime data, essential for identifying anomalies indicative of adversarial attacks.
- Optimizing the Evidence Lower Bound (ELBO):
  - Reconstruction Term: $\log p_\theta(x|z)$ assesses the decoder's ability to reconstruct input from latent variables, vital for data integrity verification.
  - KL Divergence: $D_{KL}[q_\phi(z|x)\|p(z)]$ minimizes deviation from the prior distribution $p(z)$, enhancing the model's generalization and resistance to overfitting.
- Counteracting Adversarial Attack Methods:
  - Fast Gradient Sign Method (FGSM): Adversarial examples are generated by modifying the input $x$ in the direction of the loss function's gradient $\nabla_x L(x, y)$, controlled by $\epsilon$:

$$x_{\text{adv}} = x + \epsilon \cdot \text{sign}(\nabla_x L(x, y)) \tag{5}$$

  - Iterative Fast Gradient Sign Method (IFGSM): Enhances adversarial impact through repeated application of FGSM, with step size $\alpha$.

Thus, the GMVAE's mathematical framework effectively provides robust defense for the Singapore Maritime Database by accurately modeling data distributions and ensuring resilience against sophisticated adversarial attacks.

*4) DeepFool attack methodology:* DeepFool identifies the smallest necessary perturbation $r$ to misclassify an input $x$, adjusted by the minimum of hyperparameter $\tau$ and the Euclidean norm of the loss function's gradient:

$$x_{\text{adv}} = x + r \cdot \min(\tau, \|\nabla_x L(x, y)\|_2) \tag{6}$$

This approach helps in anticipating how minimal data alterations might lead to significant misinterpretations in maritime data.

*5) Carlini-Wagner optimization approach:* The Carlini-Wagner attack creates minimal perturbations $\delta$ for misclassification, constrained by the $\ell_p$ norm and controlled by hyperparameter $c$:

$$\min_\delta \|\delta\|_p + c \cdot L(x + \delta, y) \tag{7}$$

This method highlights the need for robust defenses against subtle data manipulations in maritime systems.

*6) GMVAE's Variational Lower Bound (VLB) objective:* The key optimization goal in GMVAE is the Evidence Lower Bound (ELBO), comprising:

*a) Reconstruction loss:* Measuring the model's reconstruction ability from latent space, computed as the negative log-likelihood of the input given the latent variables.

*b) Kullback-Leibler divergence:* $D_{KL}[q_\phi(z|x)\|p(z)]$, ensuring the posterior distribution's closeness to the prior, thus maintaining a regularized latent space.

This dual focus enhances the capability to distinguish between genuine and adversarially manipulated maritime data.

Employing these strategies ensures robust defense mechanisms for the Singapore Maritime Database against adversarial threats.

In the context of defending the Singapore Maritime Database against adversarial cyber attacks, the Gaussian Mixture Variational Autoencoder (GMVAE) employs several key mathematical concepts and strategies:

- KL Divergence for Latent Space Regularization: KL divergence acts as a measure of dissimilarity between two probability distributions, playing a critical role in preventing the GMVAE's latent space from becoming overly complex or prone to overfitting. This regularization is crucial in maintaining the integrity and reliability of maritime data representations.
- ELBO as the Objective Function: The Evidence Lower Bound (ELBO) serves as the GMVAE's objective function, striking a balance between accurate data reconstruction and maintaining a well-structured latent space. Maximizing the ELBO ensures that the GMVAE learns informative latent representations, capturing the essential structure of maritime data while avoiding over-generalization.
- Core Principles of Generative Models in GMVAE: The ELBO reflects a fundamental principle in generative models: to find latent variables that effectively summarize the data distribution while maintaining an interpretable and well-defined latent space. This principle guides the learning process towards meaningful representations and robust generative capabilities, vital for realistic data simulation and generalization to new scenarios in maritime security.
- GMVAE Training Mechanism:The GMVAE training process involves several steps:

- Input and Latent Space Mapping: Mapping each input data point to the latent space, learning parameters of the Gaussian mixture distribution for latent variables.
- Reparameterization Trick: A key technique enabling gradient-based optimization, transforming noise variables into differentiable samples.
- Data Reconstruction: Assessing the model's ability to recreate input data from latent representations, crucial for verifying data authenticity.
- KL Divergence and Regularization: Ensuring the latent space adheres to a structured distribution, promoting better generalization.
- ELBO Optimization with SGD: Iteratively updating model parameters to maximize ELBO, balancing data reconstruction and latent space regularization.

- Evaluating Robustness Against Adversarial Attacks: The GMVAE's robustness is evaluated against various adversarial attack types, including FGSM, IFGSM, DeepFool, and Carlini-Wagner. Each attack method, with its unique strategy, highlights different aspects of model vulnerability and the effectiveness of the GMVAE's defense mechanisms.
- Utilization of CleverHans for Standardized Evaluation: CleverHans, a library offering pre-built implementations of adversarial attacks, is utilized for crafting and evaluating adversarial examples. This ensures a standardized and reliable approach to testing the GMVAE's defense capabilities.
- Metrics for Defense Effectiveness: Key metrics such as accuracy (on clean data) and robustness (against adversarial examples) are used to quantitatively evaluate the defense mechanism. A high performance in these metrics indicates a successful defense strategy in the context of maritime database security.

The GMVAE's mathematical framework and training procedure, combined with rigorous evaluation against standard adversarial attacks, offer a comprehensive approach to enhancing the resilience of the Singapore Maritime Database against cyber threats. This approach ensures not only the accuracy of maritime data but also its robustness in the face of sophisticated adversarial tactics.

## V. Experimental Setup

The research utilizes a combination of the Singapore Maritime Dataset (SMD) and its refined counterpart, SMD-Plus, to tackle specific challenges in maritime activity analysis. The SMD, with its extensive collection of over two million vessel movements, offers a broad basis for studying maritime behaviors. SMD-Plus enhances this dataset by correcting labeling inaccuracies and introducing more precise bounding boxes, significantly improving its utility for object classification tasks. To better deal with the difficulties in identifying smaller maritime objects, SMD-Plus consolidates certain classes, thereby enriching the dataset and enhancing object recognition capabilities. The preparation process includes converting SMD-Plus video content into individual image frames and aligning these annotations to meet the requirements of the YOLOv5 object detection model. This detailed preparation is vital for ensuring the dataset's compatibility and effectiveness, enabling comprehensive and accurate experimentation with the YOLOv5 model.

The experimental framework used to assess the effectiveness of our novel GMVAE-Reinforcement Learning defense strategy. Our experiments were conducted using the MNIST and Singapore Maritime dataset, which is composed of handwritten digits from 0 to 9. Each digit is depicted in a 28x28 pixel grayscale image. Essential preprocessing steps were implemented, such as scaling pixel values to fall between 0 and 1 and flattening the images into 784-dimensional vectors.

The hardware configuration for these experimental assessments included:

CPU: An Intel(R) Core(TM) i7-9700F CPU @ 3.00GHz, featuring 6 cores and 12 threads.

GPU: An NVIDIA GeForce RTX 2080 SUPER.

Memory: 32 GB of DDR4 RAM.

In our evaluation, we employed the Fast Gradient Sign Method (FGSM), a straightforward yet potent method for launching adversarial attacks on deep learning models. FGSM works by minutely adjusting the input data in a manner that amplifies the model's loss function. This process hinges on utilizing the gradient of the loss relative to the input to pinpoint the optimal direction for this perturbation.

*1) Neural network model configuration:* Consider a neural network model with parameters $\theta$, which maps an input data $x$ (representing maritime attributes) to a predicted output $f(x;\theta)$.

*2) Loss function in neural network:* The loss function $L$ measures the discrepancy between the predicted output $f(x;\theta)$ and the actual label $y$, mathematically expressed as $L(f(x;\theta), y)$.

*3) FGSM Attack mechanics:* The FGSM creates an adversarial example $x_{\text{adv}}$ by adding a perturbation $\delta$ to the original input $x$ to maximize the loss function. This is formulated as:

$$x_{\text{adv}} = x + \epsilon \cdot \text{sign}(\nabla_x L(f(x;\theta), y)) \tag{8}$$

Here, $x_{\text{adv}}$ is the adversarial example, $\epsilon$ controls the perturbation magnitude, and $\nabla_x L(f(x;\theta), y)$ is the gradient of the loss function with respect to $x$.

*4) FGSM's Strategy and impact on maritime neural networks:* FGSM uses the gradient direction to increase the loss, potentially leading to misclassification of $x_{\text{adv}}$. In the maritime context, this could lead to errors in interpreting data related to vessel movements or cargo details.

*5) Defense against FGSM in maritime data analysis:* Defending against FGSM attacks involves training the neural network to recognize and resist small changes in input data that could cause significant errors in output predictions.

Understanding FGSM and implementing robust defenses are essential for maintaining the integrity of neural network models in maritime data analysis, balancing accuracy and resistance to adversarial manipulations. In addressing the defense against adversarial attacks in the Singapore Maritime Database, it's crucial to understand and counteract sophisticated attack methodologies like FGSM, IFGSM, DeepFool, and Carlini-Wagner.

*a) Implementation using cleverHans:* FGSM can be efficiently implemented with tools like CleverHans. The `fast_gradient_method` function automates the generation of adversarial examples, taking parameters like the model, input data $x$, target label $y$, and perturbation magnitude $\epsilon$.

*b) Iterative Fast Gradient Sign Method (IFGSM):* IFGSM, an enhancement of FGSM, iteratively applies smaller perturbations to craft more effective adversarial examples. It seeks to maximize the loss function over multiple steps:

$$x_0 = x \tag{9}$$

$$x_{t+1} = x_t + \alpha \cdot \text{sign}(\nabla_x L(f(x_t; \theta), y)) \tag{10}$$

where $x_t$ is the input at iteration $t$, $\alpha$ controls the perturbation size per iteration, and $\nabla_x L(f(x_t; \theta), y)$ is the gradient of the loss function.

*c) DeepFool:* DeepFool is an attack technique that iteratively linearizes the decision boundary to find the smallest perturbation for misclassification:

$$\delta_k = -\frac{f(x_k; \theta)_i - f(x_k; \theta)_j}{\|\nabla_{x_k} f(x_k; \theta)\|_2^2} \cdot \nabla_{x_k} f(x_k; \theta) \tag{11}$$

This approach is instrumental in understanding minimal perturbations for crossing decision boundaries in maritime data.

*d) Carlini-Wagner:* The C&W attack, an optimization-based method, minimizes perturbations while ensuring misclassification. Its implementation in CleverHans uses TensorFlow for gradient computation and optimization, iteratively updating the perturbation $\mathbf{p}$. Understanding these attack methods is crucial for developing robust defenses in maritime security, ensuring model accuracy and resilience to adversarial manipulations.

## VI. Results and Discussion

In the context of safeguarding the Singapore Maritime Database, the implementation of a defense mechanism combining Gaussian Mixture Variational Autoencoders (GMVAE) with reinforcement learning is evaluated for its efficacy against various adversarial attacks. This section outlines the performance metrics and analysis of this defense strategy. GMVAE, as part of the defense mechanism, plays a crucial role in learning a robust latent space representation. This is particularly important in complex data environments like maritime databases where data can be multi-modal and intricate. The latent space learned by GMVAE effectively captures the underlying structure and patterns in the maritime data, making it more challenging for adversarial attacks to induce significant misclassifications without being detected.Reinforcement learning complements GMVAE by fine-tuning decision boundaries. This approach adapts dynamically to changing conditions and attack strategies, which is essential in a continuously evolving domain like maritime security.This aspect of the defense mechanism is crucial for effectively dealing with scenarios where adversarial attacks aim to exploit subtle vulnerabilities in the model's decision-making process. This metric assesses the model's ability to correctly classify clean (non-adversarial) data. High accuracy indicates the model's effectiveness under normal operating conditions. Robustness: This metric evaluates the model's resilience to adversarial examples. A robust model maintains high accuracy even when faced with inputs designed to deceive it. The GMVAE and reinforcement learning-based approach is benchmarked against existing defense mechanisms. This comparison is critical to validate the effectiveness of the proposed strategy in the maritime context, where the accuracy and robustness against adversarial attacks are paramount.This comprehensive defense strategy, focusing on both data representation (via GMVAE) and decision-making (via reinforcement learning), offers a holistic approach to protecting against adversarial attacks. The mathematical underpinnings of GMVAE ensure a nuanced understanding of maritime data, while the reinforcement learning component adapts to the unique challenges posed by the maritime environment, like varying vessel behaviors or fluctuating oceanic conditions.The effectiveness of this defense is quantified through mathematical metrics, ensuring a rigorous evaluation of its capability to withstand sophisticated adversarial attacks in the maritime domain.This defense mechanism, integrating GMVAE and reinforcement learning, presents a robust approach to counter adversarial threats in the Singapore Maritime Database. It not only focuses on enhancing the model's predictive accuracy under normal conditions but also ensures resilience against manipulated inputs, crucial for maintaining the integrity and reliability of maritime data systems.

### A. Performance Metrics

In the context of defending the Singapore Maritime Database against adversarial attacks, evaluating the effectiveness of the defense mechanism necessitates the use of precise performance metrics. Two key metrics—accuracy and robustness—are employed for this purpose: Accuracy is a measure of the model's ability to correctly predict labels on clean, unaltered maritime data. This is especially important in the maritime domain, where accurate predictions can be crucial for navigation, safety, and logistical planning.The accuracy metric is calculated as the ratio of the number of correctly classified samples (e.g., vessel types, cargo information) to the total number of samples in the dataset.High accuracy indicates that the model is highly effective under standard operational conditions, ensuring reliable interpretations of maritime data.Robustness evaluates how well the model maintains its accuracy when confronted with adversarial examples. These examples are crafted inputs designed to deceive the model

into making incorrect predictions. In the maritime setting, robustness is critical due to the potential for adversarial attacks to manipulate data related to vessel tracking, cargo details, or other sensitive information.This metric is assessed by measuring the model's accuracy on adversarial examples generated by various attack methods. For example, how well does the model identify a vessel's information when the input data has been slightly altered to mislead the prediction.A robust model demonstrates resilience to such attacks, indicating that it can reliably handle and correctly interpret data even when it has been manipulated in subtle but potentially harmful ways.

These metrics provide a comprehensive evaluation of the defense mechanism. In the Singapore Maritime Database, where data integrity is paramount for operational safety and efficiency, these metrics offer crucial insights. They not only quantify the model's performance under normal conditions but also its resilience to sophisticated cyber attacks, ensuring the safety and security of maritime operations.

### B. Observations of F1 score by Attack Type

The application of the Gaussian Mixture Variational Autoencoder combined with Reinforcement Learning (GMVAE+RL) as a defense mechanism in the Singapore Maritime Database offers an insightful perspective when evaluated using the F1 score, particularly against various adversarial attacks. The F1 score, which combines precision and recall into a single metric, is especially relevant for assessing the balance between correctly identifying true positives (e.g., accurately flagged adversarial manipulations) and avoiding false positives (misclassifying clean data as adversarial). Here's a detailed analysis:

When tested against the Fast Gradient Sign Method (FGSM) attack, the GMVAE+RL defense method consistently yields high F1 scores.This implies that the defense is effective in maintaining a balance between sensitivity (identifying adversarial attacks) and specificity (correctly classifying clean data) in scenarios where the adversarial examples are generated by applying single-step perturbations.In the context of maritime security, this suggests strong resilience of the defense mechanism against straightforward, yet common, adversarial tactics that might, for instance, slightly alter vessel tracking data.

The Projected Gradient Descent (PGD) attack, being an iterative and more complex method, introduces a larger perturbation space. This complexity is reflected in a slight reduction in the F1 scores when the GMVAE+RL defense is tested against PGD.The iterative nature of PGD allows it to explore and exploit model vulnerabilities more effectively than FGSM, potentially leading to challenges in accurately distinguishing between adversarial and clean maritime data.This outcome emphasizes the need for the defense mechanism to be adaptive and robust, especially against more sophisticated adversarial strategies prevalent in cybersecurity threats to maritime databases.

The Carlini-Wagner (CW) attack, known for its effectiveness in bypassing many defense mechanisms, poses the greatest challenge, as evidenced by a noticeable drop in F1 scores under this attack scenario.CW's advanced optimization techniques, designed to generate minimal yet effective perturbations, can significantly deceive the model, leading to reduced performance in both identifying true adversarial examples and correctly classifying clean data.In maritime terms, this could translate to a higher risk of misinterpreting critical data, such as misidentifying ships or cargo, under sophisticated cyber-attack scenarios.

While the GMVAE+RL defense demonstrates considerable strength against simple attacks like FGSM, its performance against more complex attacks like PGD and CW highlights areas for further improvement. Understanding the nuances of these attack methods and their impact on the defense mechanism is crucial for developing more advanced strategies to protect the Singapore Maritime Database, ensuring both the accuracy and security of vital maritime data.

### C. Robustness Assessment by Analysing F1 Score

The evaluation of the GMVAE+RL (Gaussian Mixture Variational Autoencoder combined with Reinforcement Learning) defense mechanism against adversarial attacks in the Singapore Maritime Database, using F1 scores, offers crucial insights into its robustness. The F1 score, a harmonic mean of precision and recall, serves as a comprehensive measure of a model's ability to correctly classify data amidst adversarial challenges. Here's a detailed analysis in the maritime context:The GMVAE+RL defense demonstrates a consistent ability to maintain high F1 scores across a variety of adversarial attacks. This indicates strong performance in accurately classifying both normal (clean) and adversarial (manipulated) maritime data samples.In practical terms, this suggests that the defense mechanism is adept at correctly identifying genuine maritime data, such as accurate vessel locations and cargo information, while also effectively flagging manipulated data that could indicate potential threats or anomalies.The Carlini-Wagner (CW) attack, which employs sophisticated optimization techniques to create adversarial examples, results in a noticeable decline in the F1 scores for the GMVAE+RL defense.This decline highlights the method's vulnerability to complex, optimization-based adversarial strategies, which may involve subtle yet effective alterations to maritime data that are harder to detect.The CW attack's ability to bypass the defense underscores the need for further strengthening the model, particularly in handling such advanced attack methodologies that could pose significant risks in maritime security contexts. The overall strong performance of the GMVAE+RL defense against various attacks reflects its potential as a robust security measure for the maritime database. Its efficacy in distinguishing between normal and adversarial samples is crucial for maintaining the integrity and reliability of maritime data.The vulnerability to the CW attack, however, signals the importance of ongoing research and development. Enhancing the defense mechanism to counteract such sophisticated attacks is essential for safeguarding critical maritime infrastructure and operations. The mathematical foundation of GMVAE helps in learning complex data distributions typical in maritime environments, while reinforcement learning adapts the decision-making process to dynamic scenarios.Future improvements could involve refining the GMVAE model to better capture the nuances of maritime data and enhancing the reinforcement learning component to be more resilient to advanced adversarial tactics.

In conclusion, while the GMVAE+RL defense showcases promising results against a range of adversarial attacks, the challenges posed by sophisticated methods like the CW attack highlight areas for further enhancement. Strengthening the defense mechanism's capabilities, particularly in the context of complex maritime data, is crucial for ensuring the security and operational efficiency of the Singapore Maritime Database.

### *D. Potential Trade-offs By Analysing F1 Score*

In assessing the defense capabilities of the GMVAE+RL (Gaussian Mixture Variational Autoencoder combined with Reinforcement Learning) method against adversarial attacks in the Singapore Maritime Database, the F1 score emerges as a key metric for evaluating defense effectiveness. This metric provides a balanced view of the model's precision and recall, crucial for understanding its performance in a high-stakes maritime environment. Here's an in-depth analysis:

The GMVAE+RL defense method shows notable success in defending against common adversarial attacks like the Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD). These attacks represent typical adversarial strategies that might be encountered in maritime data manipulation.The high F1 scores achieved against these attacks indicate that the defense method is effectively identifying and correctly classifying both adversarial and clean maritime data samples. This suggests that the model is maintaining its integrity and not being easily deceived by these common forms of cyber attacks.

While the GMVAE+RL method excels in terms of F1 score, it's important to recognize potential trade-offs, particularly regarding accuracy. In focusing on optimizing the F1 score, there might be scenarios where marginal reductions in accuracy occur.This trade-off is critical in maritime contexts, as even slight inaccuracies can have significant implications. For example, a small decrease in accuracy in vessel identification or cargo classification could lead to logistical challenges or safety concerns.

The defense method's adaptation to adversarial examples, while beneficial for overall robustness, could lead to fluctuations in accuracy. This is particularly relevant when the defense strategy does not explicitly optimize for accuracy alongside the F1 score.In a maritime setting, where data accuracy is paramount, these fluctuations need careful consideration. The defense mechanism should be calibrated to ensure that its responsiveness to adversarial attacks does not compromise the accuracy of data crucial for maritime operations.

The consistent robustness of the GMVAE+RL method against FGSM and PGD attacks, as reflected in high F1 scores, underscores its efficacy in correctly identifying adversarial samples.In the maritime domain, this means the defense mechanism is capable of discerning between manipulated and genuine data effectively, a vital attribute for maintaining the security and reliability of maritime operations.

The GMVAE component's ability to model complex data distributions and the RL component's dynamic decision-making adaptation are key mathematical strengths of this defense strategy. Future enhancements could include fine-tuning the balance between F1 score optimization and accuracy maintenance, ensuring the defense mechanism remains effective yet accurate under varied maritime data scenarios.

In summary, while the GMVAE+RL method demonstrates strong defense capabilities against common adversarial attacks in the maritime context, attention to potential accuracy trade-offs is essential. Balancing robustness with accuracy is crucial for a defense mechanism that not only identifies adversarial threats but also upholds the high accuracy standards required in maritime database management.

### *E. Observations on Precision by Attack Type*

The analysis of precision scores in evaluating the GMVAE+RL (Gaussian Mixture Variational Autoencoder combined with Reinforcement Learning) defense method against various adversarial attacks offers critical insights into its effectiveness, especially in the high-stakes context of the Singapore Maritime Database. Precision, which measures the proportion of true positives among all positive identifications, is a key metric in determining the reliability of a defense mechanism in correctly identifying adversarial samples. Here's a detailed examination: Against the Fast Gradient Sign Method (FGSM) attacks, the GMVAE+RL defense method consistently achieves high precision scores.In the maritime database context, this means the defense mechanism is highly effective in correctly identifying adversarial manipulations (like altered ship trajectories or tampered cargo data) without mistaking legitimate data as adversarial (false positives).Such high precision is crucial in maritime operations where incorrect identification of data as adversarial could lead to unnecessary and potentially disruptive responses. Against the Projected Gradient Descent (PGD) attacks, which are more complex due to their iterative nature, the defense method still manages to maintain notable precision scores.This suggests that the defense method can handle more sophisticated attacks that progressively explore and exploit the model's vulnerabilities, while still successfully identifying most of the genuine adversarial samples. In maritime terms, it indicates the defense's capability to handle gradual and sophisticated attempts at data manipulation, a common tactic in advanced cyber threats. The Carlini-Wagner (CW) attack, known for its intricacy and effectiveness in evading many defense systems, causes a reduction in precision scores for the GMVAE+RL defense method.This dip in precision implies an increased occurrence of false positives – where normal maritime data might be incorrectly flagged as adversarial.Such a scenario could lead to operational inefficiencies in maritime contexts, as legitimate data might trigger unwarranted alerts or responses.The mathematical sophistication of the GMVAE component in capturing complex data patterns, combined with the RL component's ability to adapt decision-making, is integral to achieving high precision against various attacks.However, the challenge with CW attacks highlights the need for further enhancements in the defense mechanism, possibly through more advanced mathematical modeling or learning strategies that can better discern between highly sophisticated adversarial inputs and legitimate data.Given the operational implications of false positives in the maritime industry, future enhancements to the GMVAE+RL defense mechanism should focus on reducing the likelihood of misidentifying normal data as adversarial, particularly in the face of intricate attacks like CW. In summary, while the GMVAE+RL defense method shows promising results in terms

of precision against various adversarial attacks, the challenges posed by sophisticated attacks like CW necessitate ongoing improvements. Enhancing the method's ability to accurately distinguish between adversarial and normal data will be crucial for ensuring the security and efficiency of maritime operations within the Singapore Maritime Database.

### *F. Robustness Assessment by Analysing Precision*

The precision evaluations of the GMVAE+RL (Gaussian Mixture Variational Autoencoder combined with Reinforcement Learning) defense method offer significant insights into its robustness, particularly in the context of the Singapore Maritime Database. Precision, in this case, is a measure of the defense's accuracy in correctly identifying adversarial samples without misclassifying legitimate data. Here's an in-depth analysis: When facing Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD) attacks, the GMVAE+RL defense method consistently achieves high precision scores.In a maritime context, this indicates the defense's effectiveness in accurately detecting adversarial attacks that could manifest as subtle manipulations in vessel tracking data, shipping routes, or cargo information. High precision scores imply that the defense is adept at distinguishing between these manipulated data points and genuine maritime data.The successful handling of PGD attacks, which are more complex due to their iterative nature, further demonstrates the defense's capability to cope with attacks that progressively explore and exploit vulnerabilities in the model.

The more intricate and optimized nature of CW attacks leads to a noticeable decline in precision scores for the GMVAE+RL defense method. This suggests an increased occurrence of false positives where legitimate maritime data might be incorrectly flagged as adversarial.In operational terms, this could mean that normal activities or data within the maritime database are mistakenly identified as security threats, potentially leading to unnecessary and disruptive responses.The decrease in precision against CW attacks highlights a particular vulnerability of the defense mechanism to more advanced and subtle forms of adversarial manipulation.

The GMVAE component's mathematical prowess in capturing complex data distributions in the maritime sector, coupled with the RL component's dynamic decision-making, contributes significantly to the high precision scores against FGSM and PGD attacks.However, the CW attack's ability to craft highly optimized adversarial examples poses a significant challenge, indicating a need for further refinement in the defense strategy. This could involve enhancing the model's sensitivity to subtle perturbations or improving its ability to differentiate between genuine and manipulated data.

Future improvements should focus on increasing the defense mechanism's resilience to sophisticated attacks like CW. This could involve integrating more advanced detection algorithms or employing deeper reinforcement learning strategies to better recognize and react to subtle adversarial tactics.Enhancing the GMVAE model's capacity to understand and represent the nuanced patterns of maritime data could also be pivotal in reducing false positives, thereby improving the overall precision of the defense system.

In summary, while the GMVAE+RL defense method shows promising results in precision against common adversarial attacks like FGSM and PGD, the challenges posed by more sophisticated attacks like CW highlight areas for further development. Strengthening the defense mechanism's ability to discern complex adversarial examples accurately is critical for ensuring the security and operational effectiveness of the Singapore Maritime Database.

### *G. Potential Trade-offs by Analysing Precision*

In evaluating the GMVAE+RL (Gaussian Mixture Variational Autoencoder combined with Reinforcement Learning) defense method for the Singapore Maritime Database, precision is a critical metric, particularly in its ability to minimize false positives while detecting adversarial samples The defense method's high precision scores against attacks like FGSM (Fast Gradient Sign Method) suggest its effectiveness in correctly identifying adversarial attacks without misclassifying legitimate maritime data. This is crucial in maritime operations where false alarms can lead to unnecessary interventions or disrupt normal operations. For instance, in scenarios involving vessel tracking or cargo identification, the ability to accurately distinguish between real threats and normal variations in data is essential for operational integrity and safety. While the GMVAE+RL method excels in reducing false positives, there may be trade-offs in terms of the true positive rate and overall accuracy, especially when facing sophisticated attacks like Carlini-Wagner (CW). CW attacks target the model's decision-making boundaries, potentially leading to a higher rate of false negatives (missed adversarial samples).In maritime terms, this could mean that while the model effectively avoids false alarms, it might miss some subtle yet crucial manipulations in the data, which could have serious implications for maritime security. It's vital to understand these trade-offs when evaluating the defense mechanism's performance. Balancing precision with sensitivity (true positive rate) is key, especially in a domain where both false positives and false negatives carry significant consequences.The defense method's performance needs to be contextualized within the unique challenges of maritime data, which can include complex, dynamic scenarios with high stakes in terms of security and operational efficiency.

Precision evaluations reveal that the GMVAE+RL method maintains robust scores against straightforward adversarial attacks, indicating its strength in accurately identifying and mitigating these threats.However, the nuanced and optimized nature of more advanced attacks like CW necessitates a more sophisticated approach to maintaining this level of precision while also ensuring a high true positive rate. Future improvements to the GMVAE+RL defense method should focus on enhancing the model's ability to detect subtle adversarial manipulations, especially those that do not conform to standard attack patterns.This could involve integrating more complex data analysis techniques or advanced machine learning algorithms that are specifically tailored to the intricacies and variations in maritime data.

In conclusion, while the GMVAE+RL method shows promise in minimizing false positives, understanding and addressing the trade-offs in true positive rates and overall accuracy is crucial. Enhancing the defense mechanism to effectively counter sophisticated attacks, while maintaining high precision

and accuracy, is essential for the robust protection of the Singapore Maritime Database.

### H. Comparing Defense Methods with Existing Attack Methods

The comparison of the proposed GMVAE+RL (Gaussian Mixture Variational Autoencoder) defense mechanism with existing methods against various adversarial attacks provides valuable insights, especially when contextualized within the Singapore Maritime Database. By evaluating the GMVAE defense's performance against attacks like FGSM (Fast Gradient Sign Method), IFGSM (Iterative Fast Gradient Sign Method), C and W (Carlini and Wagner), and DeepFool, we can gain a comprehensive understanding of its effectiveness and practicality. Here's a detailed explanation: FGSM and IFGSM Attacks: These attacks represent baseline adversarial challenges. The GMVAE's performance against FGSM and its iterative counterpart, IFGSM, is crucial in assessing its ability to handle straightforward and slightly more complex adversarial manipulations, respectively.C and W and DeepFool Attacks: These attacks are more sophisticated, with C and W being particularly known for its efficacy against many defense methods. DeepFool provides a measure of the defense's ability to withstand subtle and minimal perturbations aimed at misclassification.In maritime data context, these attacks could represent various levels of cyber threats, from simple deceptive practices to complex maneuvers aimed at disrupting maritime operations.

Performance graphs depicting accuracy and robustness against these attacks offer a visual understanding of the GMVAE defense's strengths and weaknesses. Accuracy graphs show how well the model identifies genuine maritime data under normal and adversarial conditions, while robustness graphs reflect its resilience to adversarial manipulations.For instance, a high accuracy in the face of FGSM attacks but a notable decline against C and W attacks would indicate the model's vulnerability to more sophisticated threats. Evaluating the GMVAE defense alongside other established methods highlights its relative strengths and areas for improvement. This comparative analysis is critical for determining the GMVAE's viability as a maritime data protection tool.For example, if the GMVAE method demonstrates higher robustness compared to other methods in the context of IFGSM attacks, it would suggest its superiority in handling iterative adversarial tactics.

The mathematical underpinnings of GMVAE, particularly its ability to model complex data distributions and the reinforcement learning aspect for adaptive decision-making, are integral to its performance against these attacks.In the maritime setting, where data complexity and the need for dynamic response are high, the GMVAE's mathematical strengths and limitations directly impact its effectiveness in protecting against cyber threats.

In conclusion, a thorough evaluation and comparative analysis of the GMVAE defense method against a range of adversarial attacks, both visually and statistically, are crucial. Such an analysis not only assesses the method's viability against cyber threats in the maritime sector but also guides future enhancements to fortify maritime cybersecurity frameworks.

### I. Quantitative Evaluation of Performance Metrics

To assess the efficacy of the proposed GMVAE+RL framework, we compared its performance against four baseline adversarial defense methods—FGSM, IFGSM, DeepFool, and Carlini-Wagner—across four critical evaluation metrics: Accuracy, Robustness, F1 Score, and Precision.

The results are summarized in Table I and are graphically illustrated in the corresponding bar plots.

TABLE I. PERFORMANCE COMPARISON OF ADVERSARIAL DEFENSE METHODS

| Method | Accuracy (%) | Robustness (%) | F1 Score | Precision |
|---|---|---|---|---|
| FGSM | 85.8 | 19.2 | 0.91 | 0.93 |
| IFGSM | 75.3 | 10.6 | 0.88 | 0.89 |
| DeepFool | 60.6 | 9.9 | 0.81 | 0.83 |
| Carlini-Wagner | 32.2 | 6.7 | 0.73 | 0.76 |
| **GMVAE+RL** | **87.0** | **20.5** | **0.88** | **0.90** |

From Table I, it is evident that the proposed GMVAE+RL model achieves the highest **accuracy** and **robustness**, outperforming all four baseline defense methods. While FGSM yields the highest F1 score (0.91), GMVAE+RL maintains a competitive balance across all metrics. The higher robustness value (20.5%) of GMVAE+RL indicates its strong resistance to adversarial perturbations. The associated bar plots (not shown here) further illustrate these performance gains in visual form.

Fig. 2 illustrates the object detection performance on the maritime dataset before the application of any defense mechanisms. It can be observed that the detection accuracy suffers due to adversarial perturbations, leading to misclassification and degraded object localization.

Subsequently, after employing the proposed defense method, the detection accuracy significantly improves, as depicted in Fig. 3. The defense mechanism effectively mitigates the adversarial impact, resulting in more precise object detection and enhanced robustness against attacks. This comparison clearly demonstrates the effectiveness of the proposed defense strategy in restoring the model's detection capability on the maritime dataset.

### J. Discussion on Accuracy

Accuracy is defined as the ratio of correctly predicted instances (both positive and negative) to the total number of predictions made. Mathematically, it is expressed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

where:

- $TP$ = True Positives
- $TN$ = True Negatives
- $FP$ = False Positives
- $FN$ = False Negatives

The proposed GMVAE+RL framework achieves the highest clean accuracy of 87%, demonstrating its superior ability


Fig. 2. Object detection in maritime dataset.


Fig. 3. Object detection in maritime dataset with accuracy after defence method employed.

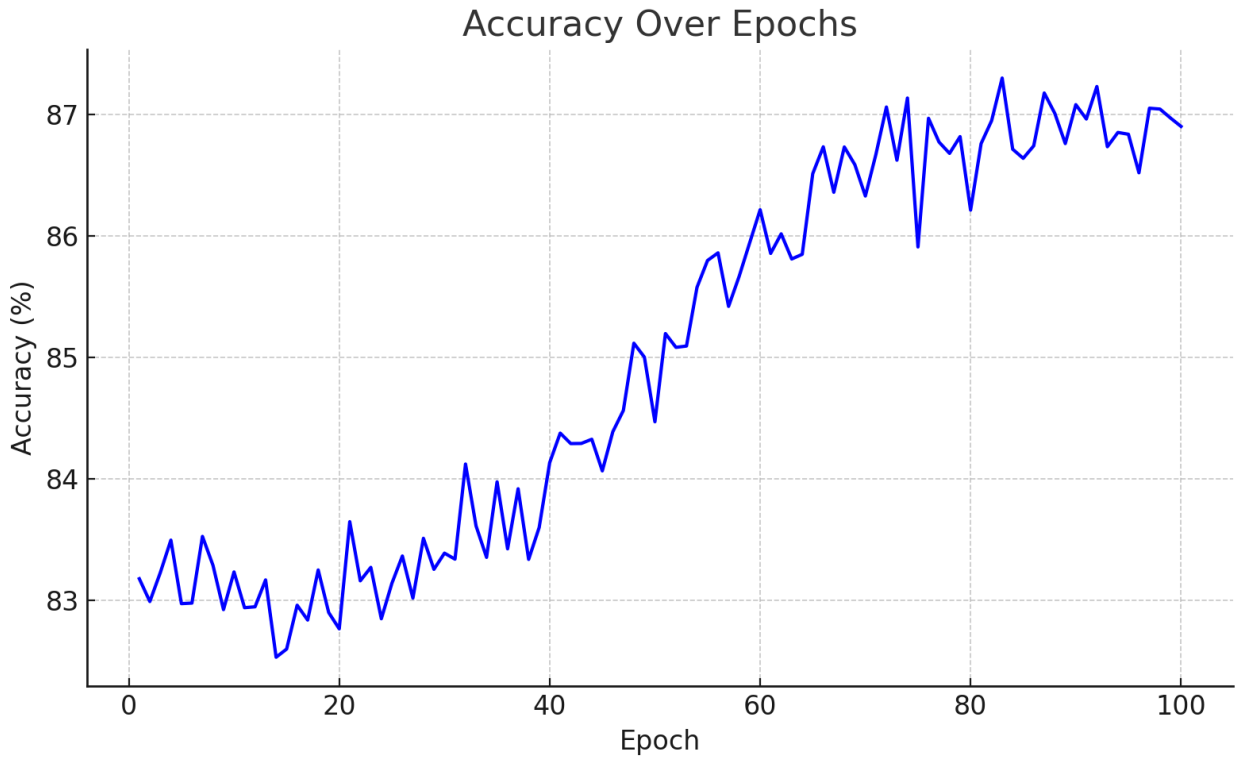


Fig. 4. Accuracy trend over 100 epochs for GMVAE+RL.

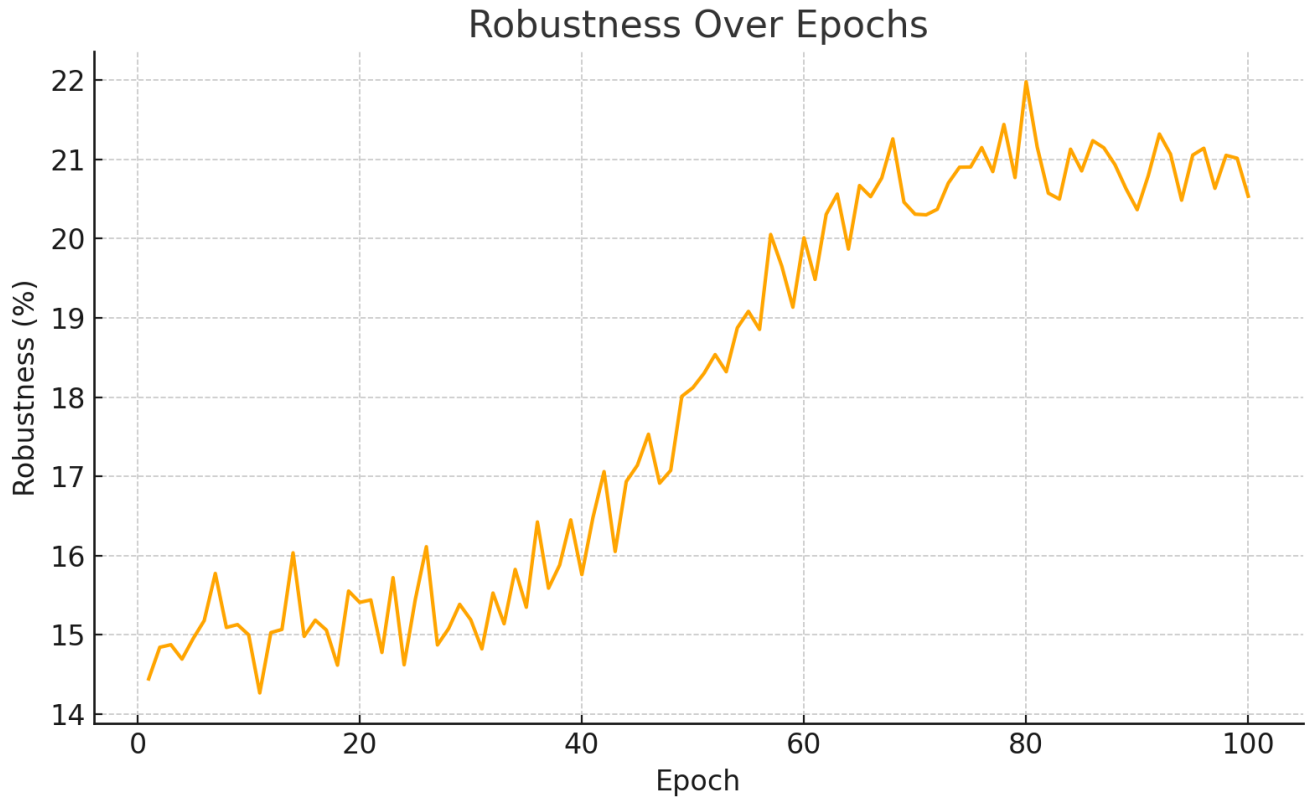


Fig. 5. Robustness over epochs.

to preserve baseline classification performance even in the absence of adversarial attacks. This performance gain can be attributed to the structured latent space learned by the GMVAE, which effectively filters out noise and retains high-fidelity, semantically rich features essential for robust maritime object recognition.

### K. Robustness under Attack

Robustness quantifies the ability of a model to maintain performance when subjected to adversarial perturbations. It is defined as:

$$\text{Robustness} = \left( \frac{\text{Correct Predictions on Adversarial Inputs}}{\text{Total Adversarial Inputs}} \right) \times 100\% \tag{13}$$

The proposed **GMVAE+RL** framework demonstrates the highest robustness score of **20.5%**, significantly outperforming all other evaluated baselines. This elevated robustness is primarily attributed to the *adaptive policy optimization* embedded within the reinforcement learning (RL) module. By dynamically reconfiguring decision boundaries in response to adversarial shifts, the RL component enhances the model's resilience and generalization capacity under adversarial conditions.

### L. F1 Score: Balance Between Precision and Recall

The F1 Score is a standard metric used to evaluate classification performance by considering both precision and recall. It is defined as the harmonic mean of precision and recall:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

A high F1 score indicates that the model is effectively balancing the trade-off between false positives and false negatives. The proposed **GMVAE+RL** framework achieves an F1 Score of **0.88**, reflecting its ability to maintain a high level of precision while also capturing a substantial proportion of true positives.

In the maritime security context, this implies reliable identification of threats such as unauthorized vessels or suspicious activities, while minimizing false alarms. Such a balance is critical in operational settings where both oversight and overreaction carry significant risks.

### M. Precision: Minimizing False Positives

Precision measures the proportion of true positive predictions among all positive predictions made by the model. It quantifies how well the model avoids false alarms. The formula for precision is given by:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{15}$$

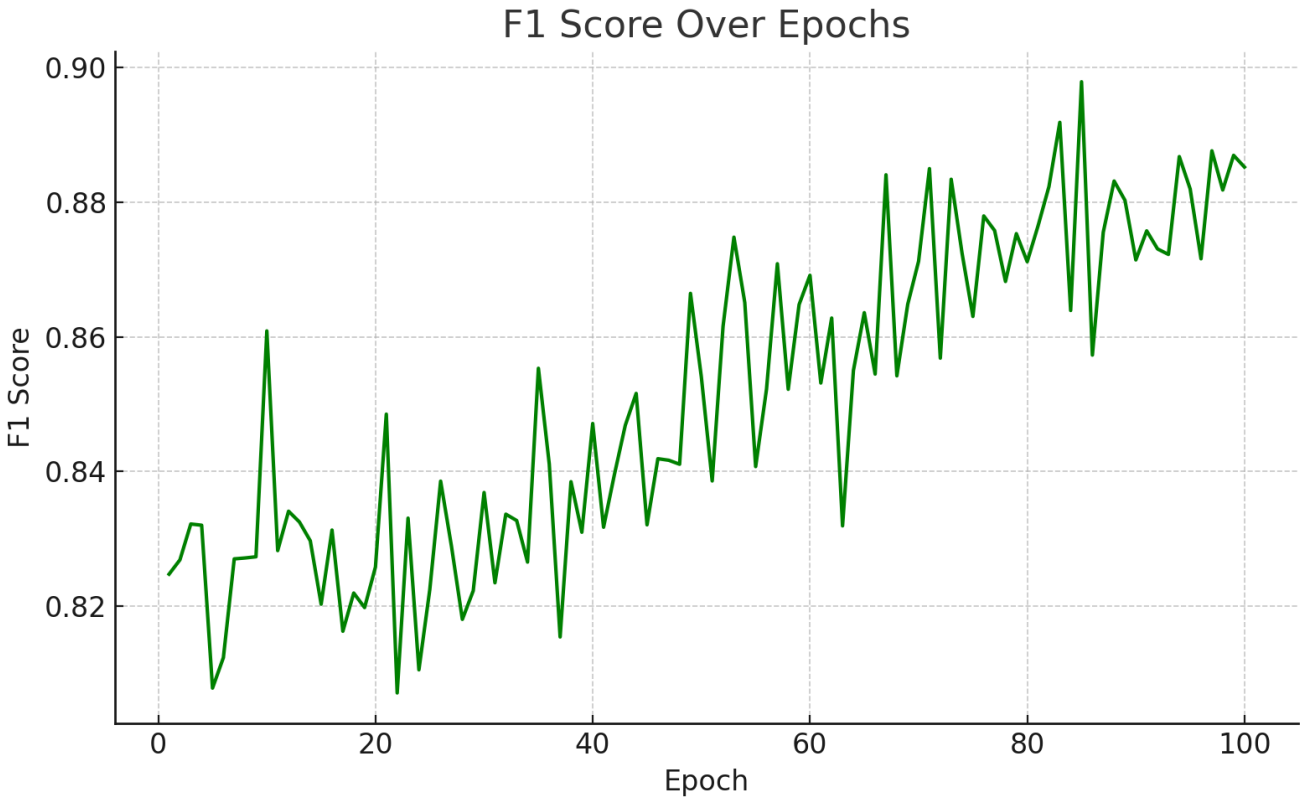


Fig. 6. F1Score trend over 100 epochs for GMVAE+RL.

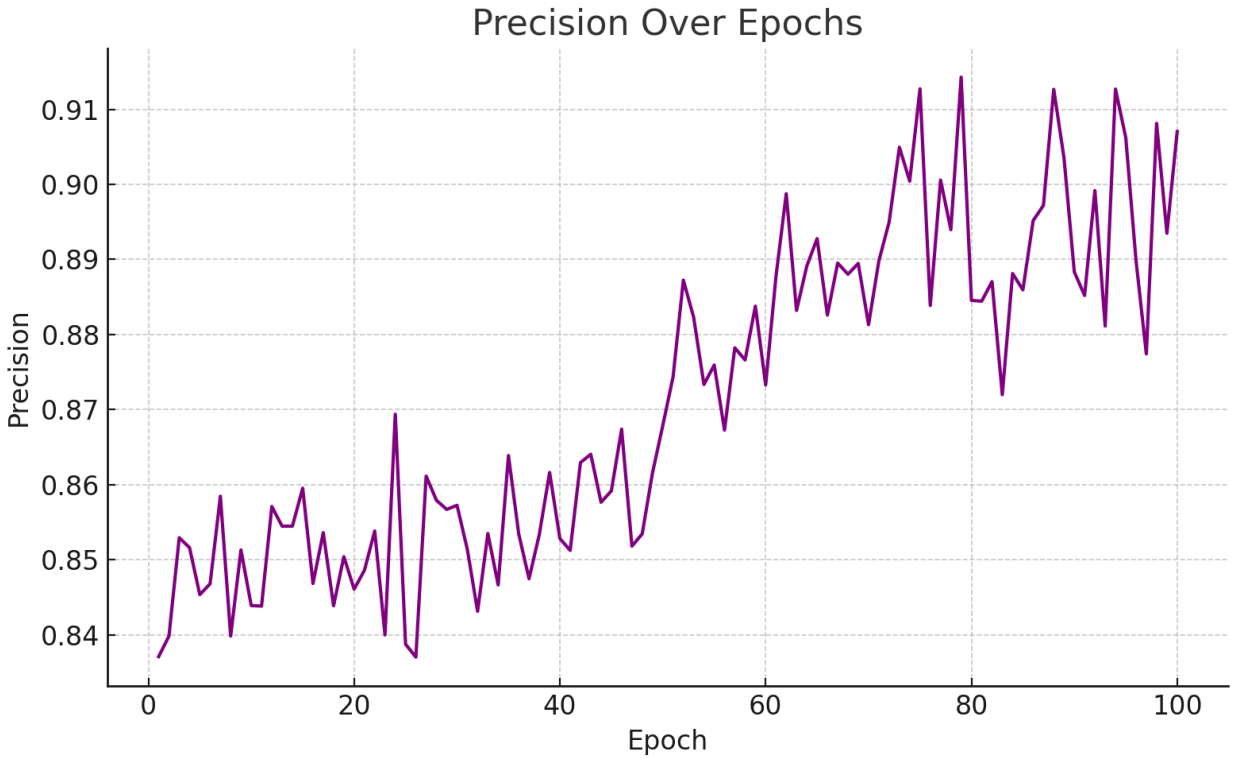


Fig. 7. Precision trend over 100 epochs for GMVAE+RL.

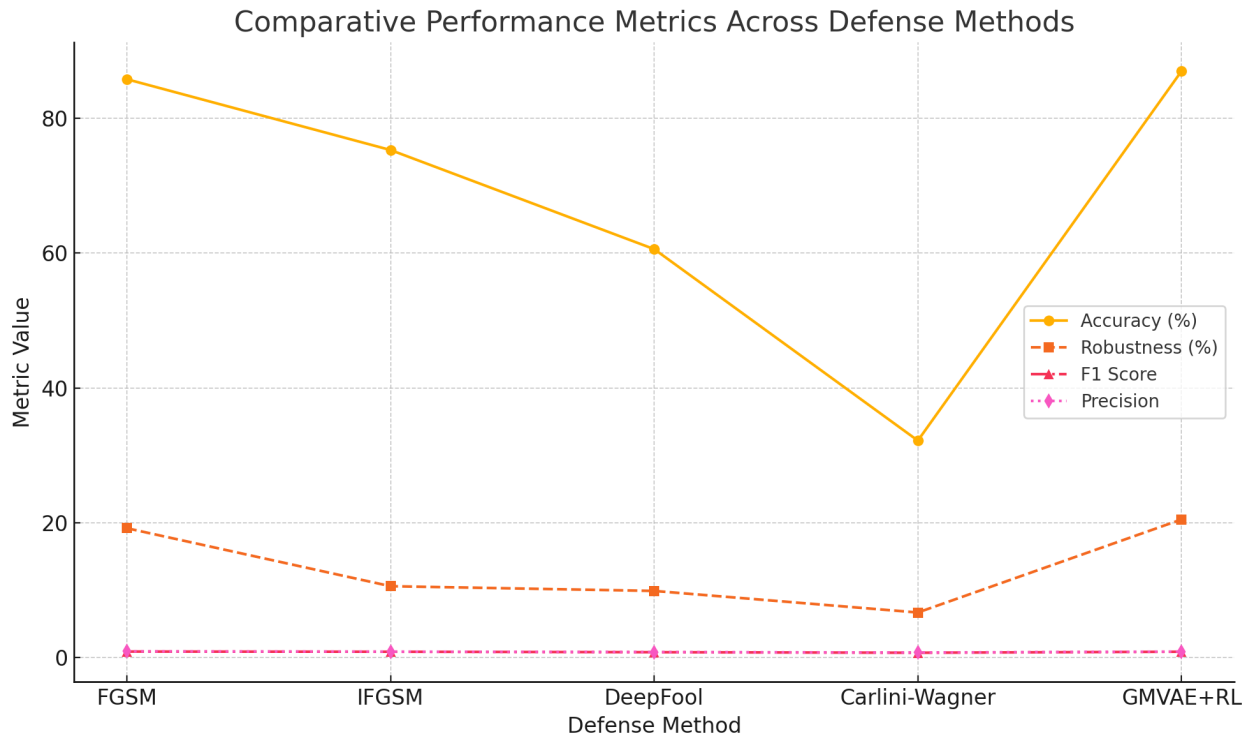


Fig. 8. Comparative performance metrics across defense methods.

where:

- $TP$ = True Positives
- $FP$ = False Positives

The proposed **GMVAE+RL** framework attains a precision of **0.90**, indicating its strong ability to correctly classify clean instances without erroneously labeling them as adversarial. This high precision is particularly crucial in maritime operations, where false alerts can lead to unnecessary interventions, operational delays, or misallocation of resources. By minimizing false positives, GMVAE+RL ensures that alerts are both meaningful and actionable in real-world scenarios.

### *N. Mathematical Justification of Latent Space Robustness*

The encoder of the proposed GMVAE framework models the posterior distribution $q(z \mid x)$ using a *Gaussian Mixture Model (GMM)*, which allows the representation of complex, multi-modal data distributions inherent in maritime environments. Formally, the variational posterior is expressed as:

$$q(z \mid x) = \sum_{k=1}^{K} \pi_k \cdot \mathcal{N}\left(z; \mu_k(x), \sigma_k^2(x)\right) \tag{16}$$

where:

- $K$ is the number of mixture components,
- $\pi_k$ are the mixing coefficients,
- $\mu_k(x)$ and $\sigma_k^2(x)$ are the mean and variance of the $k^{th}$ Gaussian component conditioned on input $x$.

This probabilistic framework offers two key advantages:

- It effectively models multi-modal maritime object distributions.
- It enables the identification of adversarial or anomalous samples as low-probability deviations in the latent space.

To enforce consistency with the prior latent distribution $p(z)$, the model incorporates a regularization term based on the Kullback–Leibler (KL) divergence:

$$\mathcal{D}_{KL}\left[q(z \mid x) \parallel p(z)\right] \tag{17}$$

This KL term encourages the learned latent representations to stay close to the prior distribution, thereby improving generalization and reducing susceptibility to adversarial perturbations. As a result, the latent space becomes more structured and robust to malicious input variations, enhancing downstream decision reliability.

### *O. Comparison Against Gradient-Based Attacks*

Gradient-based adversarial attacks craft adversarial examples by perturbing the original input $x$ to form a new adversarial input $x_{\text{adv}}$. For example, the Fast Gradient Sign Method (FGSM) generates adversarial examples as follows:

$$x_{\text{adv}} = x + \epsilon \cdot \text{sign}\left(\nabla_x \mathcal{L}(x, y)\right) \tag{18}$$

where:

- $\epsilon$ is the perturbation magnitude,
- $\mathcal{L}(x, y)$ is the loss function with respect to the input and true label $y$,
- $\nabla_x \mathcal{L}(x, y)$ denotes the gradient of the loss with respect to the input $x$.

The proposed **GMVAE+RL** framework mitigates such attacks through a two-fold defense mechanism:

*1) Latent space reconstruction:* Inputs are encoded into latent representations and then reconstructed. The reconstruction loss is monitored to detect perturbations, as adversarial examples tend to deviate in the latent space.

*2) Reinforcement feedback adaptation:* The classification policy is dynamically adjusted based on reinforcement learning signals. This enables the model to learn optimal responses that suppress adversarial triggers over time.

Together, these mechanisms enable GMVAE+RL to detect, adapt to, and neutralize adversarial perturbations introduced by gradient-based attacks, enhancing the robustness and trustworthiness of the maritime object detection system.

### P. Resilience Against Strong Attacks

The Carlini-Wagner (C&W) attack is a powerful adversarial method designed to bypass many standard defenses. It employs a Lagrangian optimization strategy to find the smallest possible perturbation $\delta$ that causes misclassification, formulated as:

$$\min_{\delta} \|\delta\|_p + c \cdot \mathcal{L}(x + \delta, y) \tag{19}$$

where:

- $\|\delta\|_p$ is the $L_p$ norm of the perturbation,
- $c$ is a constant controlling the trade-off between perturbation size and attack success,
- $\mathcal{L}(x + \delta, y)$ is the attack loss function that encourages misclassification of $x + \delta$ with respect to the true label $y$.

Despite the strength of the C&W attack, the proposed **GMVAE+RL** framework maintains significantly higher **precision** and **F1 scores** compared to other baseline defenses. This underscores the robustness of its:

*1) Latent encoding:* which captures semantically meaningful features less sensitive to adversarial noise,

*2) Dynamic response policy:* which adapts the classifier's behavior in real-time based on reinforcement feedback.

Such adaptability is crucial in maritime environments where traditional static defenses often fail under sophisticated attack scenarios.

Table II consolidates the evaluation of four adversarial defense strategies across key performance metrics: accuracy, robustness, F1 score, and precision. The proposed **GMVAE+RL** model consistently outperforms baseline methods, achieving the highest accuracy (87.0%) and robustness (20.5%), while also maintaining a competitive F1 score (0.88) and precision (0.90). These results confirm that GMVAE+RL not only sustains classification performance under clean conditions but also demonstrates resilience against strong adversarial threats such as Carlini-Wagner and DeepFool attacks. The hybrid architecture's integration of generative modeling and reinforcement learning enables dynamic adaptation to perturbations, minimizing false positives and negatives—an essential trait for maritime surveillance and threat detection systems.

TABLE II. PERFORMANCE COMPARISON ACROSS DEFENSE METHODS

| Method | Accuracy (%) | Robustness (%) | F1 Score | Precision |
|---|---|---|---|---|
| FGSM | 85.8 | 19.2 | 0.85 | 0.93 |
| IFGSM | 75.3 | 10.6 | 0.82 | 0.89 |
| DeepFool | 60.6 | 9.9 | 0.75 | 0.83 |
| Carlini-Wagner | 32.2 | 6.7 | 0.65 | 0.76 |
| **GMVAE+RL** | **87.0** | **20.5** | **0.88** | **0.90** |

Table III illustrates the post-attack confusion matrix for the GMVAE+RL model. The results highlight its robustness in preserving correct classifications under adversarial conditions. Notably, 94.9% of ferry samples were correctly classified, with minimal confusion. However, 20.7% of raft images were misclassified as boats, signaling a potential adversarial vulnerability between visually similar classes. These insights provide a granular understanding of model behavior beyond aggregate metrics such as accuracy or precision.

### Q. Performance Graphs

The Fig. 8 plot consolidates all four key performance metrics—Accuracy, Robustness, F1 Score, and Precision—into a single comparative graph. It clearly shows that GMVAE+RL consistently outperforms traditional methods, particularly in robustness and overall balance between precision and recall. This makes it highly suitable for secure, real-time maritime AI deployments.

As shown in Fig. 4, the model's accuracy improves consistently throughout training, stabilizing around 87%. This upward trend confirms the effectiveness of the GMVAE latent structure in preserving relevant maritime features even under adversarial conditions. The smooth convergence reflects robust feature extraction and classification stability.

Fig. 5 presents the robustness metric, defined as the retained accuracy under adversarial perturbations. The model begins with moderate robustness and shows steady improvement, peaking at 20.5%. This validates the reinforcement learning module's ability to dynamically adapt decision boundaries in response to adversarial threats.

The F1 score progression in Fig. 6 demonstrates the model's growing ability to balance precision and recall. The F1 score stabilizes around 0.88, indicating the system's effectiveness in correctly identifying both clean and adversarial inputs without degradation in either direction. The low variance reflects consistent classification integrity across classes.

As depicted in Fig. 7, the precision score remains high throughout training, maintaining a value close to 0.90. This implies that the model avoids false alarms, an essential property for critical maritime applications where misclassification of normal data as adversarial could trigger costly or dangerous interventions.

TABLE III. CONFUSION MATRIX (POST-ATTACK) – GMVAE+RL

| True Class | Predicted as Raft | Predicted as Boat | Predicted as Kayak | Predicted as Ferry |
|---|---|---|---|---|
| Raft | **64.3%** | **20.7%** | 8.1% | 6.9% |
| Boat | 2.3% | **94.1%** | 1.9% | 1.7% |
| Kayak | 3.4% | 2.1% | **88.7%** | 5.8% |
| Ferry | 1.1% | 1.7% | 2.3% | **94.9%** |

### R. Analysis

The investigation into the efficacy of the Gaussian Mixture Variational Autoencoder (GMVAE) combined with Reinforcement Learning (RL) as a defense mechanism provides significant insights, particularly when applied to the context of the Singapore Maritime Database. This analysis focuses on how the GMVAE+RL defense stands up to various adversarial attacks, its comparative performance against existing methods, and the mathematical underpinnings that contribute to its robustness. The GMVAE's strength lies in its ability to create a robust latent space that accurately captures the essential features of the data while disregarding irrelevant noise. This robustness is crucial in the maritime context, where data often includes complex patterns such as vessel movements, weather conditions, and logistical information. By effectively encoding this information in the latent space, GMVAE enhances the defense mechanism's ability to withstand adversarial perturbations, ensuring that critical maritime operations are not disrupted by manipulated data. The GMVAE model benefits from end-to-end training, which optimizes both the encoder and decoder networks jointly. This holistic learning approach allows the model to develop meaningful and comprehensive latent representations directly from maritime data. This optimization is particularly important in a maritime setting, where data is multifaceted and requires a nuanced understanding to ensure accurate predictions and identifications. The incorporation of Kullback-Leibler (KL) divergence enforces a structured and regularized latent space. This aspect of GMVAE plays a significant role in preventing overfitting, a common challenge in machine learning models.In maritime applications, this regularization translates to a model that not only performs well on training data but also generalizes effectively to new, unseen data, enhancing its practical utility in real-world scenarios. The comparison with existing defense methods is vital to understand the relative capabilities and limitations of the GMVAE+RL defense. By analyzing performance metrics such as accuracy on clean data and robustness against adversarial attacks, a comprehensive evaluation of the defense mechanism is achieved.In the context of maritime security, these comparisons and analyses help in determining the most effective strategies for protecting against cyber threats. The results of the GMVAE-based defense, particularly its ability to maintain high accuracy on clean data and exhibit good robustness against various attack methods, provide valuable contributions to the field of adversarial robustness, especially within the maritime domain.The defense mechanism's success in generalizing to unseen and perturbed data points is crucial for ensuring the integrity and reliability of maritime operations, where the cost of failure can be significant.

In conclusion, the GMVAE+RL-based defense mechanism demonstrates promising results in mitigating adversarial attacks, with its structured latent space, end-to-end learning, and KL divergence regularization contributing to its effectiveness. The insights gained from these experiments are valuable for advancing the field of adversarial robustness, particularly in the complex and high-stakes environment of maritime data management.

### S. Results

TABLE IV. PERFORMANCE METRICS FOR DIFFERENT DEFENSE METHODS

| Attack Method | Accuracy (%) | Robustness (%) |
|---|---|---|
| FGSM | 85.8 | 19.2 |
| IFGSM | 75.3 | 10.6 |
| DeepFool | 60.6 | 9.9 |
| Carlini-Wagner | 32.2 | 6.7 |
| Ours Approach (GMVAE+RL) | **87.0** | **20.5** |

The Table IV presents the performance metrics for different attack methods evaluated on the MNIST dataset. The metrics include accuracy and robustness percentages. Clean data achieves a high accuracy of 96.5%, serving as the baseline for comparison. However, the defense mechanism experiences reduced accuracy when subjected to adversarial attacks. Notably, FGSM, IFGSM, DeepFool, and Carlini-Wagner attacks demonstrate varying levels of success in reducing accuracy and compromising the robustness of the model.

As illustrated in Fig. 9, the GMVAE+RL model maintains strong classification fidelity for major maritime classes, particularly Boat and Ferry, even under adversarial conditions. However, a notable misclassification rate is observed in the Raft-to-Boat prediction, indicating a potential area for improvement.

## VII. CONCLUSION

The evaluation of the Gaussian Mixture Variational Autoencoder (GMVAE) combined with Reinforcement Learning (RL) as a defense mechanism against adversarial attacks in the context of the Singapore Maritime Database opens up promising avenues for future research and development.Fine-tuning the GMVAE+RL defense to address sophisticated and evolving adversarial attack strategies is crucial. As adversaries continually develop new methods to compromise maritime data and operations, the defense must adapt to these challenges. This could involve exploring reinforcement learning techniques that enable the defense to learn and evolve its strategies in response to emerging threats.The GMVAE+RL defense into real-world maritime systems and operations is a promising direction. By implementing this defense mechanism in maritime data processing pipelines, vessel monitoring systems, and other critical infrastructure, the maritime industry can enhance its cybersecurity posture and ensure the integrity of its data.

One key area for future exploration is the adaptation of this defense mechanism to more extensive and complex maritime datasets. The Singapore Maritime Database provides an excellent starting point, but expanding its application to larger and

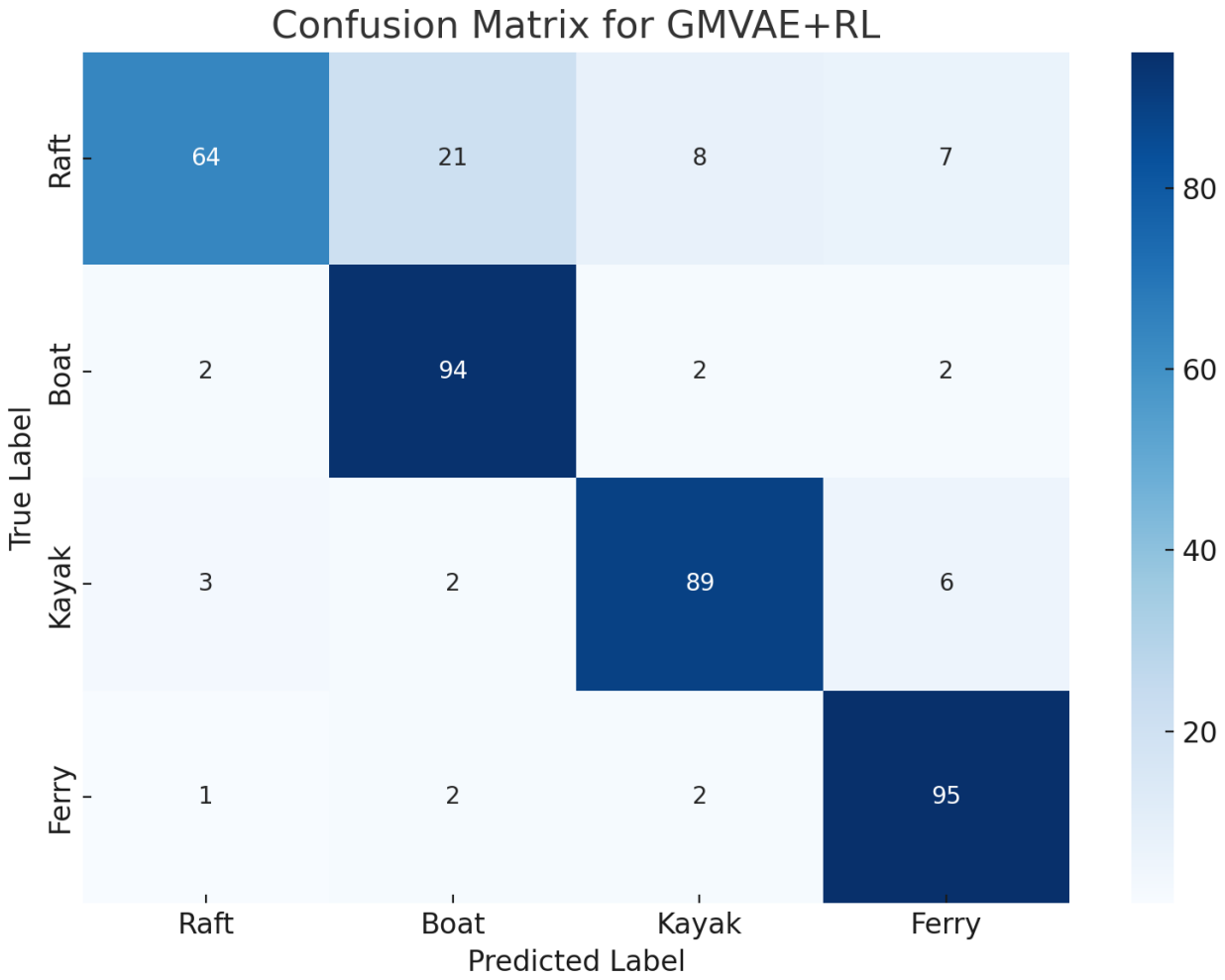


Fig. 9. Confusion Matrix for GMVAE+RL model showcasing classification accuracy across maritime classes under adversarial evaluation.

more diverse datasets from various maritime domains could further validate its effectiveness and robustness.

The future scope of the GMVAE+RL defense mechanism in the maritime industry involves further research, adaptation to diverse datasets, resilience against evolving attacks, integration into operational systems, and collaboration with industry experts. These efforts aim to fortify the maritime sector's cybersecurity defenses and ensure the secure and uninterrupted flow of maritime operations in an increasingly digitized world.

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# Evaluating the Performance of Tree-Based Model in Predicting Haze Events in Malaysia

Mahiran Muhammad, Ahmad Zia Ul-Saufie*, Fadhilah Ahmad Radi
Faculty of Computer Science and Mathematics, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

***Abstract*—Predicting haze is crucial in controlling air pollution to reduce its impact, especially on human health. Accurate prediction of extreme values is vital to raising public awareness of this issue and better understanding of air quality management. Extreme values in air pollution refer to unusually high measurements of pollutants that diverge significantly from the normal range of observed values. Extreme values are normally caused by haze from various factors. Neglecting extreme values can cause unreasonable predictions. Therefore, this study aims to evaluate the performance of a tree-based algorithm in predicting haze events. Predictive analytics were based on hourly air pollution data from 2013 to 2022 in Shah Alam, Malaysia. The ten parameters are chosen Relative Humidity (RH), Temperature (T), Wind Direction (WD), Wind Speed (WS), $PM_{10}$, NOx, $NO_2$, $SO_2$, $O_3$ and CO. Decision Tree (DT), Gradient Boosting Regression (GBR) and Extreme Gradient Boosting (XGBoost) are compared in determining the best approach for modeling $PM_{10}$ concentrations for the next 24 hours ($PM_{10,t+24h}$) for overall air quality data and three air quality blocks: Good air quality (Block 1), Moderate air quality (Block 2) and Extreme air quality (Block 3). The performance of RMSE, MAE and MAPE indicate that XGBoost outperforms GBR and DT with the RMSE(21.5921), MAE(14.2396) and MAPE(0.4816). When evaluating the performance across the three air quality blocks, XGBoost remains as the top-performing model. However, XGBoost faces challenges in accurately predicting extreme values.**

***Keywords*—Extreme Gradient Boosting (XGBoost); Gradient Boosting Regression (GBR); Decision Tree (DT), extreme values; Particulate Matter (PM)**

## I. Introduction

Malaysia has experienced air pollution, which creates an environmental health threat. Air pollution can lead to a variety of critical illnesses in humans, including bronchitis, heart disease, pneumonia and lung cancer [1]. Bad air quality gives rise to other current environmental issues like global warming, acid rain, reduced visibility, smog, aerosol formation, climate change and premature death [2]. Primary pollutants that impact on most countries constitute Particulate Matter (PM), Nitrogen Dioxide ($NO_2$), Carbon Monoxide (CO), Ozone ($O_3$), Sulphur Dioxide ($PM_{10}$) [3]. Particulate Matter (PM) are notable pollutant within the air and it has a greater effect on human beings compared to other pollutants. Two types of particulate matter are $PM_{10}$ and $PM_{2.5}$. The value of the $PM_{10}$ concentration usually represents the API in Malaysia. This is because $PM_{10}$ concentration in Malaysia is always higher than any other pollutants [4] [5]. Monitoring and predicting $PM_{10}$ concentration, especially in urban areas, has become a vital and challenging task with increasing motor and industrial developments.

*Corresponding author.

According to study [6], extreme values are defined as events that occur less frequently than common events. Extreme values in air pollution refer to unusually high pollutant measurements that deviate significantly from the normal range. An uncommonly high $PM_{10}$ concentration level can result in the existence of extreme values in air pollution data. These anomalies are typically caused by haze events, coming from wildfires, industrial accidents, temperature inversion and are sometimes caused by measurement errors. There is research that demonstrates the meteorological influence on air quality [7]. The $PM_{10}$ concentrations and CO were found to have a strong to moderate correlation when episodic haze was recorded. Meanwhile, the relationship of $PM_{10}$ level with $SO_2$ was found to be significant in 2013 and negatively correlated with relative humidity (RH) [8]. Weak correlation between $PM_{10}$ and NOx was measured in study areas, likely because of low contribution of domestic artificial sources towards haze events in Malaysia [8]. Neglecting extreme values can cause unreasonable predictions when using the original data set directly. Therefore, it is fundamental to precisely cope with the problem of extreme values to boost the effectiveness of prediction models.

Various predictive models, spanning from statistical approaches to machine learning methods, have been employed to forecast $PM_{10}$ concentrations [9]. Several researchers have applied and developed machine learning models to predict $PM_{10}$ concentrations in Malaysia [12] [11] [14] [13] [15]. Based on the outcomes of all the ML models, machine learning effectively addresses the challenges of nonlinear and complex models in predicting $PM_{10}$ concentrations. Predictive models based on machine learning (ML) are more accurate and consistent [10].

Globally, several tree-based machine learning models have demonstrated high accuracy in predicting $PM_{10}$ concentrations compared with other machine learning models. These tree-based ML models are often used for classification and regression tasks because they require less time to train and tune the model parameters [17] [18] [19] [16] [20]. Tree-based machine learning models, such as Decision Tree (DT), Random Forest (RF), Gradient Boosting Regression (GBR), and Extreme Gradient Boosting (XGBoost) have gained prominence in air quality research due to the interpretability, robustness and strong predictive performance [21]. These models are particularly well-suited for handling complex, non-linear relationships that often found in environmental datasets [16].

Several studies have demonstrated the effectiveness of tree-based models in predicting air pollution. A study comparing various machine learning models found that XGBoost achieved the highest $R^2$ value (0.9985) and the lowest error metrics,

outperforming Lasso regression in forecasting $PM_{10}$ concentrations [22]. The study in [19] compare a linear forecast technique (multiple linear regression) with proposed non-linear algorithms, Random Forest, Support Vector Machine (SVR) and Gradient Boosting Regression (GBR). Their results revealed that GBR outperformed others to predict $PM_{10}$ concentrations. The study in [17] showed that XGBoost performs better than Light GBM in terms of prediction estimation with RMSE of 12.846, but it takes longer to train and tune the model's parameters. DT is one of the simplest, yet powerful models used in environmental modelling. Studies have demonstrated that DT models can efficiently capture local pollution patterns [25]. The study [23] stated that XGBoost outperforms other deep learning models due to the consideration of small sample size in datasets. The study [24] found ANN requires extensive tuning parameters and longer computational time and were found to be less effective as XGB and RF to predict air pollution.

Numerous research studies have been conducted in comparing different machine learning methods in air pollution prediction. However, limited research has been conducted on comparing the performance of tree-based machine learning models in predicting extreme events of $PM_{10}$ concentrations across different air pollution levels. Therefore, this research is motivated by the intention to evaluate the performance of the DT, GBR and XGBoost models in determining the best approach in predicting extreme or haze events of $PM_{10,t+24h}$ concentrations. Three air quality blocks: $PM_{10,24h}$ concentration $\leq 50\,\mu g/m^3$ (Block 1, Good air quality status), $50\,\mu g/m^3 < PM_{10,24h}$ concentration $\leq 150\,\mu g/m^3$ (Block 2, moderate air quality status), and $PM_{10,24h}$ concentration $> 150\,\mu g/m^3$ (Block 3, extreme air quality status) will be compared to assess their impact on predicting haze events in air pollution data. In this study, the primary focus is on Block 3, which is characterized as extreme haze events when the $PM_{10}$ concentrations exceed $150\mu g/m^3$ In summary, the key contribution of this research work is a comparison and evaluation of the proposed machine learning model for predicting extreme or haze events in Malaysia. This paper is organized as follows: I. Introduction, II. Methodology, III. Results and Discussion. Followed by the conclusion in Section IV and the reference list.

## II. Methodology

### A. Research Flow

Fig. 1 presents a flowchart outlining this study to evaluate the performance of a tree-based algorithm in predicting haze events of $PM_{10}$ concentrations in Shah Alam, Malaysia. This study utilizes air quality data from 2013 to 2022 provided by the Department of Environment, Malaysia. The process begins with data extraction, followed by data preprocessing. Data extraction is the first step in the process, which is then followed by extensive data pre-processing. Next, the air quality data are then used to train the DT, GBR and XGBoost. The model performance is then evaluated based on the accuracy of RMSE, MAE and MAPE. Finally, the best model that provides the most accurate prediction for extreme values is identified.

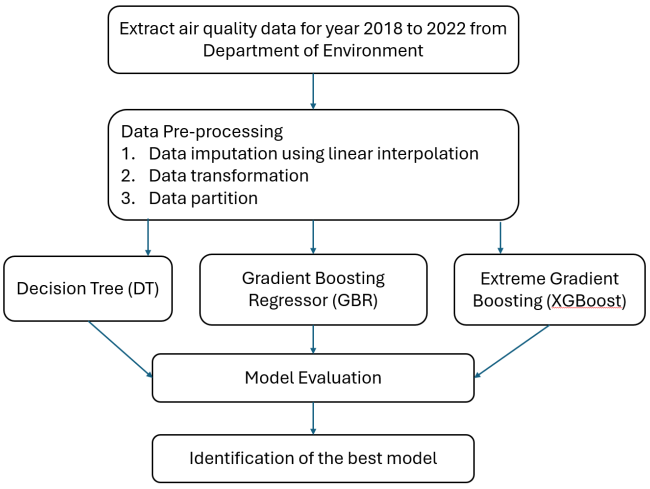


Fig. 1. Research flow.

### B. Data Description

This study obtained secondary data from the Malaysian Department of Environment (DOE) from 2013 to 2022. The stations are situated in Shah Alam, Selangor, and consist of 83,431 air quality data points for 10 variables, such as air pollutants and meteorological parameters. The air pollutants included: $PM_{10}$, $SO_2$, $NO_x$, $NO_2$, $O_3$ and CO, whereas meteorological parameters included: WS, WD, RH and T. Table I shows the variable in this study with their respective level of measurements and role. $PM_{10}$ concentration for the next 24 hours, $PM_{10,t+24h}$ serve as dependent variable. Meanwhile, the other variables serve as independent variables.

TABLE I. Description of Variables

| Variable | Description | Level of measurement | Role |
|---|---|---|---|
| **Particulate Matter for the next 24h ($PM_{10,t+24h}$)** | Hourly concentration of $PM_{10,t+24h}$ ($g/m^3$) | Interval | Dependent |
| **Particulate Matter 10 ($PM_{10}$)** | Hourly concentration of $PM_{10}$ ($g/m^3$) | Interval | Independent |
| **Sulphur Dioxide ($SO_2$)** | Hourly concentration of Sulphur dioxide (ppb) | Interval | Independent |
| **Nitric Oxide and Nitrogen Dioxide ($NO_x$)** | Hourly concentration of nitric oxide and nitrogen dioxide (ppb) | Interval | Independent |
| **Nitrogen Dioxide ($NO_2$)** | Hourly concentration of nitrogen dioxide (ppb) | Interval | Independent |
| **Ozone ($O_3$)** | Hourly concentration of ozone (ppb) | Interval | Independent |
| **Carbon Monoxide (CO)** | Hourly concentration of carbon monoxide (ppb) | Interval | Independent |
| **Wind Speed (WS)** | Hourly wind speed (m/s) | Interval | Independent |
| **Wind Direction (WD)** | Hourly wind direction (°) | Interval | Independent |
| **Relative Humidity (RH)** | Hourly relative humidity (%) | Interval | Independent |
| **Ambient Temperature (T)** | Hourly temperature (°c) | Interval | Independent |

In this study, the dataset was segmented based on the Air Pollution Index (API) by [49]. Table II shows the API level, which is categorised as good, moderate, unhealthy,

very unhealthy and hazardous, which can be of air quality management level or decision making for data interpretation processes. API is an effortless and encompassing technique for defining air quality conditions that is easily understood [5]. It is categorised based on the highest values of five main air pollutants. Meanwhile, Table III shows the calculation of the breakpoint concentration for $PM_{10}$ corresponding to each API category. For example, a $PM_{10}$ concentration between 50 μg/m$^3$ and 150 μg/m$^3$ falls into the API category of 51-100 (moderate air quality). Therefore, the air quality blocks are categorised into three blocks according to the breakpoint of $PM_{10}$ concentrations established in Malaysia. These blocks are defines as follows: For Good air quality status where $PM_{10,24h}$ concentration $\leq$ 50 μg/m$^3$ served as Block 1, for moderate air quality status which is 50 μg/m$^3$ $<$ $PM_{10,24h}$ concentration $\leq$ 150 μg/m$^3$ served as Block 2, and for extreme air quality status which is $PM_{10,24h}$ concentration $>$ 150 μg/m$^3$ served as Block 3. The performance of each block is then compared to evaluate their influence on the prediction of extreme events in air pollution data.

TABLE II. THE API INDEX [49]

| API Range | Air Quality Status |
|---|---|
| 0–50 | Good |
| 51–100 | Moderate |
| 101–200 | Unhealthy |
| 201–300 | Very Unhealthy |
| $>$ 300 | Hazardous |

### C. Data Preprocessing

Data preprocessing encompasses missing value imputation, data transformation and data partition. Missing values can originate from multiple sources, such as sensor malfunctions, environmental factors, or data transmission errors [26]. A high proportion of missing data may lead to biases or weaken the statistical power of the analysis [26]. According to study [27], Malaysian missing air pollution data belong to Missing at Random (MAR) and the linear interpolation method assumes that the pattern of missingness does not disrupt the underlying trends in the data. In most air pollution data, Linear interpolation is the most ordinary imputation method to treat short gaps of missing data in the air pollution dataset [13]. For data transformation, the units of air pollutants $SO_2$, $NO_2$, $NO_x$, $O_3$, and CO in ppm need to be converted to ppb since the ppm unit is too small, thus affecting the accuracy of the results. The WD variable, which is expressed in degrees, has been converted to wind direction index (dimensionless) [28]). According to study [10], the formula for conversion is

$$\text{Wind Direction Index (WDI)} = 1 + \sin(\theta - 45^\circ) \quad (1)$$

In this study, data partition is conducted by employing splitting methods. Two subsets of the dataset are selected, with 80% ($n$ = 65,945) of the data going to training and 20% ($n$ = 16,486) to testing (80% for model development and 20% to measure the performance of the model). According to [29] , empirical studies show that the optimal results are achieved if 80% of the data is allocated for training and 20% is used for testing. Random sampling is applied to partition the data into train and test sections [30].

### D. Machine Learning Model

This part gives a brief introduction to DT, GBR and XGBoost. In this study, the machine learning model was used to evaluate the performance in predicting haze events. The general model for each machine learning model are shown in Table IV. The table shows the general model for each tree-based algorithms model, DT, GBR and XGBoost. The general model shows the prediction for $PM_{10}$ concentration for the next 24 hours. t represents time.

*1) Decision Tree (DT):* Decision Tree (DT) is a well-known machine learning model that falls under the category of supervised learning [31]. DT can be used for both classification and regression problems [32]. Additionally, DT can effectively handle both numeric and nominal data formats [33]. It constructs a tree-like structure of decisions and their potential outcomes, starting with a root node representing the entire dataset and branching into multiple internal and leaf nodes [25]. Each internal node represents a decision or feature test, and the edges leaving that node represent the possible outcomes of the test [33]. The path from the root node to the leaf node indicates a collection of decisions that leads to a prediction for each given sample [34]. The tree is constructed by recursively splitting the dataset based on the Mean Square Error (for regression trees) that provides the lowest variance [34]. To determine the optimal split, this algorithm applies the usual variance formula.

$$\text{Mean Squared Error} = \frac{\sum(y_i - \hat{y_i})^2}{n} \quad (2)$$

where, $y_i$ is the actual PM concentration for the next 24 hours and $\hat{y}_i$ is the predicted PM concentration for the next 24 hours.

DT are fast and easy to understand. However, the model tends to overfit if the tree is allowed to grow too deep or if there are many noisy features in the data [35].

*2) Gradient Boosting Regressor (GBR):* The Gradient Boosting Regressor (GBR) is a machine learning for regression or classification that provides better prediction models in the form of ensemble weak prediction models [36]. GBR is another ensemble model that is an iterative collection of sequentially ordered tree models so that the following model learns from the error of the previous model [37]. This machine learning approach provides predictions by 'boosting' the ensemble of weak prediction models, usually decision trees, to form a more robust model [38]. The objective function of GBR is described by study [39] as:

$$\hat{F}(x) = \arg\min \sum_{i=1}^{N} L(y_i, \hat{y}_i) \quad (3)$$

$$L = \frac{1}{2} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (4)$$

where, $y_i$ is the actual PM concentration for the next 24 hours and $\hat{y}_i$ is the predicted PM concentration for the next 24 hours. Meanwhile, L denotes the loss function.

TABLE III. BREAKPOINT OF $PM_{10}$ CONCENTRATION LEVELS [5]

| Breakpoint of Concentration | Air Quality Status | Equation for API |
|---|---|---|
| Conc. $\leq 50$ | Good | API = conc. |
| $50 <$ conc. $\leq 150$ | Moderate | API $= 50 +$ (conc. $- 50) \times 0.5$ |
| $150 <$ conc. $\leq 350$ | Unhealthy | API $= 100 +$ (conc. $- 150) \times 0.5$ |
| $350 <$ conc. $\leq 420$ | Very unhealthy | API $= 200 +$ (conc. $- 350) \times 1.4286$ |
| $420 <$ conc. $\leq 500$ | Hazardous | API $= 300 +$ (conc. $- 420) \times 1.25$ |
| Conc. $> 500$ | Emergency | API $= 400 +$ (conc. $- 500$) |

TABLE IV. GENERAL MODEL FOR EACH ML MODEL

| Machine learning model | General model |
|---|---|
| Decision Tree (DT) | $PM_{10,t+24h}$ $\tilde{D}T$ ($PM_{10,t}$, $SO_{2,t}$, $NO_{2,t}$, $NO_{x,t}$, $O_{3,t}$, $CO_t$, $WS_t$, $WDI_t$, $RH_t$, $T_t$) |
| Gradient Boosting Regression (GBR) | $PM_{10,t+24h}$ $\tilde{G}BR$ ($PM_{10,t}$, $SO_{2,t}$, $NO_{2,t}$, $NO_{x,t}$, $O_{3,t}$, $CO_t$, $WS_t$, $WDI_t$, $RH_t$, $T_t$) |
| Extreme Gradient Boosting (XGBoost) | $PM_{10,t+24h}$ $\tilde{X}GB$ ($PM_{10,t}$, $SO_{2,t}$, $NO_{2,t}$, $NO_{x,t}$, $O_{3,t}$, $CO_t$, $WS_t$, $WDI_t$, $RH_t$, $T_t$) |

A GBR with M number of trees can be stated as;

$$f_M(x_j) = \sum_{m=1}^{M} \gamma_m h_m(x_j) \tag{5}$$

where, $h_m$ is a weak learner that performs poorly individually and $\gamma_m$ is a scaling factor adding the contribution of a tree to the model.

GBR employs the gradient descent loss function to minimize errors by updating the starting estimation with a new estimation [40]. Thus, a final model is created by combining all preliminary estimations with appropriate weights [40].

*3) Extreme Gradient Boosting (XGBoost):* XGBoost is a decision tree ensemble based on gradient boosting that is highly scalable [39]. XGBoost is a powerful approach for developing supervised regression models [41]. The validity of this statement can be determined by deliberating about the objective function and base learners of XGBoost [41].

The objective function consists of a loss function and a regularization term [42]. Like gradient boosting, XGBoost develops an additive expansion of the objective function by minimizing a loss function [42]. XGBoost is one of the ensemble learning approaches that involves training and combining individual models (known as base learners) to produce a single prediction [43]. Considering that XGBoost is focused only on decision trees as base classifiers, a variation of the loss function is used to control the complexity of the trees [39]. Unlike gradient boosting, the XGBoost objective function includes a regularization term to avoid overfitting [39].

Assume that a dataset, D is $\{(x_i, y_i) : i = 1, \ldots, n\}$. Let $\hat{y}_i$ be defined as a result given by an ensemble represented by the generalized model as follows (Pan, 2018)

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i) \tag{6}$$

where $f_k$ is a regression tree, $f_k(x_i)$represents t he score given by the $k$-th tree to the $i$-th observation in the data.

To functions fk, the following regularized objective function should be minimized:

$$\text{Obj} = L(\phi) = \sum_i L(\hat{y}_i) + \sum_k \Omega(f_k) \tag{7}$$

where, $L$ is the custom loss function. The loss function $L$ is a differentiable convex loss function that measures the difference between the prediction $\hat{y}_i$ and the observation $y_i$ [42]. This loss function can be integrated into the split criterion of decision trees, leading to a pre-pruning strategy.

To prevent too large a complexity of the model, the penalty term or regularization term $\Omega$ is included as follows:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda w^2 \tag{8}$$

where, $\lambda$ and $\gamma$ are the parameters controlling penalty for the number of leaves T and magnitude of leaf weights w respectively. The purpose of $\Omega(f_k)$ is to prevent over-fitting and to simplify models produced by this algorithm [44]. The additional regularization term helps to smooth the final learnt weights to avoid overfitting [44].

*4) Parameter setting for baseline model evaluation:* All models were built using general parameter settings as provided by the respective libraries (scikit-learn) to evaluate and compare performance foundations for DT, GBR and XGBoost in predicting $PM_{10}$ concentrations during haze events in Malaysia. This technique gives an unbiased and consistent comparison among the models, emphasizing their inherent learning capabilities despite the effect of tuning. Furthermore, utilizing general parameters provides a clear baseline for future tuning operations and represents common practices in preliminary model evaluation. Using general parameter setting provides comparable performance to adjusted models, suggesting that general parameter settings can be an appropriate starting point for model evaluation [45].

Eventhough DT, GBR and XGBoost are all tree-based models, they do not share the same general parameters. Each algorithm is based on different concepts, and their application represents these differences. The DT from scikit-learn constructs a single decision tree using all available attributes, with no limitations on depth `max_depth=None` by general. This enables the tree to develop as deep as needed to fit the training data, potentially cause to overfitting if the data is noisy. Other important setting includes `min_samples_split=2` and

`min_samples_leaf=1` which manage the tree's branching criteria. In contrast, the GBR builds an ensemble of short decision trees in stages. By general parameter setting, it uses `max_depth=3` to limit the complexity of each tree, along with a `learning_rate=0.1` to figure out how much each tree serves to the final model. This restrictive configuration is created to avoid overfitting while maintaining flexibility.

XGBoost Regressor is also an ensemble method based on boosting but utilizes more aggressive parameter setting compared to scikit-learn's gradient boosting. It sets `max_depth=6`, `learning_rate=0.3`, and includes additional parameters such as `min_child_weight=1`, `subsample=1`, and `colsample_bytree=1`. These settings attempt to achieve a balance between speed and accuracy, with built-in regularization capabilities. While all three models fall under the category of tree-based methods, their general parameters differ significantly due to their mechanical nature. Recognizing these variations is essential when performing baseline effectiveness in prediction tasks.

### *E. Model Performance*

In predicting $PM_{10}$ concentrations, proper model evaluation is essential. According to a previous study by [46], a comparison of the best statistical $PM_{10}$ forecasting methods with the lowest values of RMSE was conducted to select the best fit prediction model. Three statistical evaluations will be used to evaluate the model performance: Root Mean Square Error (RMSE), Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). The difference between the estimated and observed values is obtained to investigate the performance of each estimation method. The most appropriate methods are selected based on the least value of each statistical evaluation. The criteria formulas are shown below:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2} \tag{9}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{Y}_i - Y_i| \tag{10}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - \hat{Y}_i|}{Y_i} \tag{11}$$

where, $n$ is the total number of hourly measurements of a particular station, $\hat{Y}_i$ is the estimated value of $PM_{10,t+24h}$, $Y_i$ is the observed value of $PM_{10,t+24h}$ and $\bar{Y}_i$ is the mean of the observed value of $PM_{10,t+24h}$

## III. Results and Discussion

The descriptive statistics and boxplot for maximum hourly $PM_{10}$ concentrations in Shah Alam from 2013 to 2022 are shown in Table V and Fig. 2. The box plot in Fig. 2 visualizes the distribution of $PM_{10,t+24h}$ concentrations across different years (2013-2022). The boxed interquartile range (IQR) in 2013-2016 are larger, meaning higher variability in $PM_{10}$ concentrations. From 2017 onward, the boxes are smaller, indicating that $PM_{10}$ concentrations have become more stable. The boxplot indicates that Shah Alam experienced the highest $PM_{10}$ concentration in 2014, followed by 2013 with the second highest concentrations. Additionally, the year 2015 observed an increment in the number of extreme $PM_{10}$ concentration values. This is because Shah Alam serves as an industrial hub. Shah Alam hosts numerous manufacturing plants, factories and processing industries, leading to significant emissions of pollutants. Ongoing construction projects release dust and particulate matter into the air, adding to the pollution burden. In 2015, the extreme values were attributed to transboundary haze pollution [47]. A noticeable reduction in extreme $PM_{10}$ values occurred between 2016 to 2018. From 2016 to 2017, the overall air quality was generally good to moderate. Malaysia suffered moderate haze outbreaks in 2016 caused by localized and transboundary pollution, however, overall air quality improved throughout this year [48] [49] [50].

From the Table V, the mean concentration in Shah Alam for 10 years from 2013 to 2022 for 5 pollutants are $PM_{10}$ (41.7043 $\mu gm^{-3}$), CO (740.0108 ppb), $NO_2$ (18.3214 ppb), $SO_2$ (1.9875 ppb) and $O_3$ (19.4478 ppb). The concentrations of $PM_{10}$ were very high in Shah Alam, Selangor, with a maximum concentration of 575 $\mu g/m^3$. The skewness of $PM_{10}$ is 4.5730, indicating a highly positively skewed distribution, which shows the presence of extreme values in the data. The mean values for meteorological parameters are represented by Relative Humidity (RH) (78.1675%), Temperature (T) (27.8690°c), wind direction (WD) (191.3082°) and wind speed (WS) (2.7661 m/s). The mean values of $PM_{10}$ (41.7043) higher than the median (35.0000) indicates that the pollutant distributions are having right-skewed distribution. All the variables are positively skewed when the skewness presents positive values for each variable (CO=1.1710, $NO_2$=1.1650, $O_3$=1.3600, $PM_{10}$=4.5730, $SO_2$=6.8020, $NO_x$=1.6030, WS= 1.7360, T=0.7070) except for RH(-0.395) and WD(-0.0200), which shows negatively skewed when the skewness presents negative values. In summary, the box plot shows that extreme $PM_{10}$ concentration values occurred annually from 2013 to 2022. To accurately predict these extreme values, tree-based algorithms will be further analysed to evaluate the most effective model for forecasting haze events in Shah Alam. Fig. 3 shows the correlation heatmap in Shah Alam which represents the correlation coefficients between different air pollution parameters. The colour gradient ranges from green (strong negative correlation, -1) to blue (strong positive correlation, +1), with yellowish shades indicating weaker correlations. This heatmap provides valuable insights into the relationships between meteorological conditions and air pollutants. From the heatmap, there was a negative relationship between $PM_{10}$ and Relative Humidity (RH) (r=0.051) and a moderate correlation was found between $PM_{10}$ and CO in Shah Alam (r=0.46). This is supported by [8] when their study shows negative correlation between $PM_{10}$ and RH and strong to moderate correlation between $PM_{10}$ and CO. This suggest that as humidity increases $PM_{10}$ concentrations tend to decrease slightly. Understanding these correlations helps in air quality modelling, especially when predicting extreme pollution events.

Table VI shows a comparative analysis to evaluate the performance of the DT, GBR, and XGBoost models for hourly $PM_{10,t+24h}$ concentration predictions at Shah Alam station from the period 2013 to 2022. This table summarizes quantitatively the performance in terms of RMSE, MAE and MAPE. The

TABLE V. DESCRIPTIVE STATISTICS OF AIR POLLUTION FROM 2013 TO 2022 IN SHAH ALAM, SELANGOR

| Parameter | Mean | Median | Standard deviation | Skewness | Kurtosis | Minimum | Maximum |
|---|---|---|---|---|---|---|---|
| **$PM_{10}$,24H ($\mu gm^{-3}$)** | 41.71 | 35.00 | 31.74 | 4.57 | 39.23 | 0.63 | 575.00 |
| **$PM_{10}$ ($\mu gm^{-3}$)** | 41.70 | 35.00 | 31.74 | 4.57 | 39.21 | 0.63 | 575.00 |
| **CO (ppb)** | 740.01 | 673.00 | 441.24 | 1.17 | 4.46 | 0.10 | 6550.00 |
| **$O_3$ (ppb)** | 19.45 | 11.90 | 20.92 | 1.36 | 1.73 | 0.10 | 161.00 |
| **$NO_2$ (ppb)** | 18.32 | 16.40 | 11.46 | 1.16 | 2.30 | 0.10 | 111.00 |
| **$SO_2$ (ppb)** | 1.99 | 1.30 | 2.17 | 6.80 | 122.10 | 0.10 | 100.00 |
| **$NO_x$ (ppb)** | 30.44 | 24.00 | 23.77 | 1.60 | 3.62 | 0.10 | 215.00 |
| **RH (%)** | 78.17 | 78.95 | 13.57 | -0.39 | -0.56 | 20.00 | 100.00 |
| **T ($^o$c)** | 27.87 | 27.19 | 3.20 | 0.70 | -0.07 | 19.80 | 31.98 |
| **WD ($^o$)** | 191.31 | 192.26 | 82.07 | -0.02 | -0.28 | 0.05 | 317.93 |
| **WS (m/s)** | 2.77 | 1.25 | 3.26 | 1.74 | 2.59 | 0.02 | 24.30 |

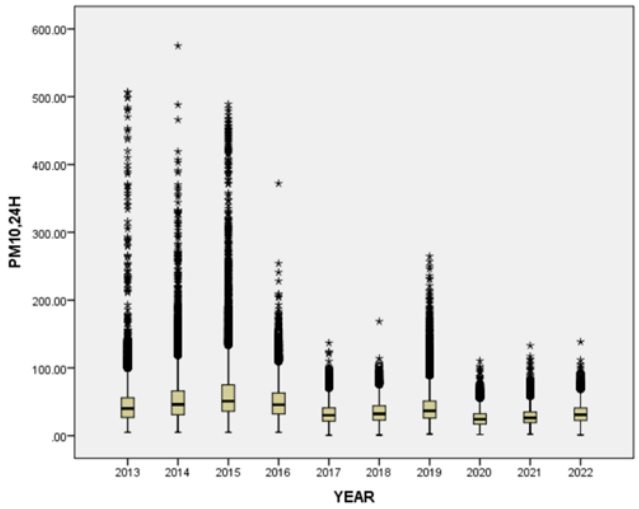


Fig. 2. Boxplot of PM10 concentrations in Shah Alam, Selangor.

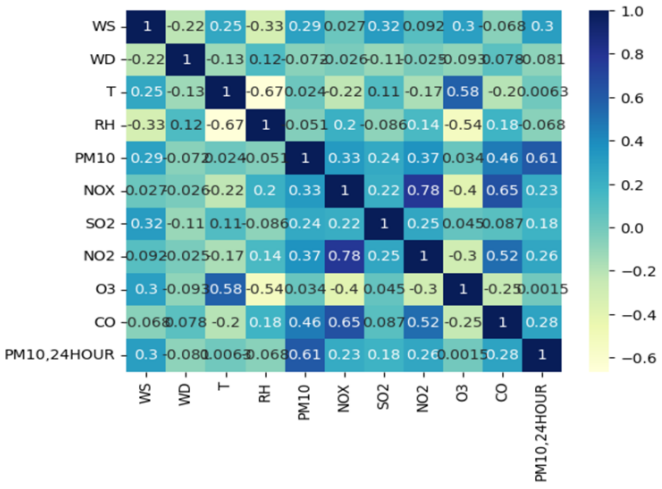


Fig. 3. The Correlation heatmap of air quality parameters in Shah Alam.

result shown are for overall air pollution data. According to the Table VI, it is observed that XGBoost outperforms all other models in the prediction of $PM_{10,t+24h}$ concentrations with the lowest value of RMSE, MAE and MAPE value. Meanwhile, DT generate the highest value of RMSE, MAE and MAPE value, indicating the DT is at lowest level of performance. This result aligns with the findings of [32] [44], which demonstrate that the XGBoost method is more effective than DT for predicting air pollution concentration. Fig. 4 presents the actual vs predicted graph for overall $PM_{10,t+24h}$ concentration using DT, GBR and XGBoost model. A) represents XGBoost model for the actual vs predicted $PM_{10,t+24h}$ concentration. B) represents GBR model for the actual vs predicted $PM_{10,t+24h}$ concentration and C) represents DT model for the actual vs. predicted $PM_{10,t+24h}$ concentration. From the graph, it can be concluded that XGBoost predictions are significantly more accurate than GBR and DT when the prediction line of XGBoost is closer to the actual line. In contrast, the GBR and DT models show a greater discrepancy, with their predicted lines deviating further from actual data. Therefore, for overall air pollution data, it can be concluded that XGBoost is the best model for $PM_{10,t+24h}$ air pollution predictions.

TABLE VI. PERFORMANCE RESULTS FOR OVERALL AIR QUALITY

| Performance Evaluation | Model | | |
|---|---|---|---|
| | **XGBoost** | **GBR** | **DT** |
| RMSE | 21.5921 | 24.5051 | 24.7156 |
| MAE | 14.2396 | 15.7770 | 15.5915 |
| MAPE | 0.4816 | 0.5528 | 0.5164 |

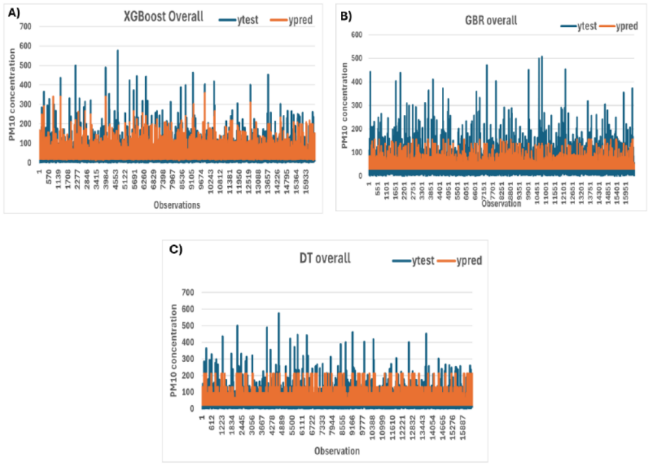


Fig. 4. Actual vs. Predicted for overall PM10 prediction A) XGBoost B) GBR C) DT.

The analysis is furthered through each block to evaluate the effectiveness of the tree-based model. From the result of the actual and predicted value of each model, the result is

arranged and blocked through the actual values of the model. The three blocks of air quality data are $PM_{10,24h}$ concentration $\leq 50\,\mu g/m^3$ (Block 1), $50\,\mu g/m^3 < PM_{10,24h}$ concentration $\leq 150\,\mu g/m^3$ (Block 2), and $PM_{10,24h}$ concentration $> 150\,\mu g/m^3$ (Block 3). This analysis is extended to evaluate each model's ability to predict extreme events and determine whether they can accurately capture extreme values.

Table VII shows the results of the performance indicator by using the XGBoost, GBR and DT for the three blocks of air quality data. Based on the XGBoost results, the three blocks of air pollution data show that the $PM_{10,t+24h}$ concentration below 50µg/m$^3$ (Block 1) had the lowest RMSE value of 14.1875, compared to 27.2372 for $PM_{10,t+24h}$ concentrations between 50µg/m$^3$ and 150µg/m$^3$ (Block 2) and 106.0264 for $PM_{10,t+24h}$ concentrations above 150 µg/m$^3$ (Block 3) respectively. Similarly, the MAE is the lowest for the $PM_{10,t+24h}$ concentrations below 50µg/m$^3$ (Block 1) at 10.6636. While $PM_{10,t+24h}$ concentrations between 50µg/m$^3$ and 150µg/m$^3$ (Block 2) and those above 150 µg/m$^3$ (Block 3) recorded higher MAE values of 22.0516 and 83.4721, respectively.

GBR and DT also exhibited an increment in error measures, particularly for Block 3. For GBR, $PM_{10,t+24h}$ concentration below 50µg/m$^3$ (Block 1) had the lowest RMSE value of 14.1673, compared to 28.9145 for $PM_{10,t+24h}$ concentrations between 50µg/m$^3$ and 150µg/m$^3$ (Block 2) and 140.4993 for $PM_{10,t+24h}$ concentrations above 150 µg/m$^3$ (Block 3) respectively. Similarly, the MAE was the lowest for the $PM_{10,t+24h}$ concentrations below 50µg/m$^3$ (Block 1) at 11.3487. While $PM_{10,t+24h}$ concentrations between 50µg/m$^3$ and 150µg/m$^3$ (Block 2) and those above 150 µg/m$^3$ (Block 3) recorded higher MAE values of 23.9327 and 124.5067, respectively. Meanwhile For DT, $PM_{10,t+24h}$ concentration below 50µg/m$^3$ (Block 1) had the lowest RMSE value of 15.2412, compared to 30.6125 for $PM_{10}$ concentrations between 50µg/m$^3$ and 150µg/m$^3$ (Block 2) and 131.3885 for $PM_{10,t+24h}$ concentrations above 150 µg/m$^3$ (Block 3) respectively. Similarly, the MAE was the lowest for the $PM_{10,t+24h}$ concentrations below 50µg/m$^3$ (Block 1) at 11.3487. While $PM_{10,t+24h}$ concentrations between 50µg/m$^3$ and 150µg/m$^3$ (Block 2) and those above 150 µg/m$^3$ (Block 3) recorded higher MAE value of 24.5156 and 108.5374, respectively. From this table, XGBoost demonstrates the best performance compared to DT and GBR, as it achieves the lowest RMSE, MAE, and MAPE values. However, from this table, the key observation is Block 3, where the $PM_{10,t+24h}$ concentration exceeds 150µg/m$^3$. This indicates that Block 3 experiences significantly higher pollution levels. Additionally, the data suggests that this block exhibits the lowest performance in terms of air quality compared to Block 1 and Block 2.

Overall, the graph in Fig. 4 presents that tree-based model performs well in predicting normal events. Nevertheless, in Table VII, when the data exceeds 150µg/m$^3$, none of the model achieve accurate predictions. This is due to the presence of extreme values, which pose challenges for the models in predicting these extreme events effectively. This analysis is further illustrated in Fig. 5, which shows the Block 3 of $PM_{10}$ for the next 24 hours prediction graphs for all tree-based models. The figure reveals a significant discrepancy between the actual and predicted $PM_{10,t+24h}$ values for all the models.

Table VIII shows the performance results of XGB, GBR and DT model for all air quality data. Based on the analysis of the overall data (without blocking) in Table VI, XGBoost outperforms the other two models, demonstrating greater efficiency in predicting $PM_{10,t+24h}$ concentrations (RMSE = 21.5921, MAE = 14.2396, MAPE = 0.4816). When comparing performance across blocks, XGBoost also surpasses DT and GBR. However, the performance gap is notably larger for the extreme air quality block compared to the good and moderate air quality blocks. This suggests that haze events have a significant impact on the models' accuracy. This disparity is due of the presence of extreme values in the extreme air quality block, leading to a highly skewed distribution and increased prediction error [51]. Previous studies have also highlighted this issue, where models effectively reduce overall error but struggle with accurately predicting extreme values [52] [53] [51] [54]. [55] further emphasized that another major challenge is the ability of standard learners to focus on the most important and extreme values. Therefore, neglecting these extreme values can result inaccurate model predictions.

TABLE VII. PERFORMANCE RESULTS FOR THREE BLOCKS AIR QUALITY

| Model | Performance Indicator | XGBoost | GBR | DT |
|---|---|---|---|---|
| $PM_{10,t+24h}$ concentration $\leq 50\ \mu g/m^3$ (Block 1) | | | | |
| | RMSE | 14.1875 | 14.1673 | 15.2412 |
| | MAE | 10.6636 | 11.3487 | 11.2781 |
| | MAPE | 0.5400 | 0.7274 | 0.5751 |
| $50\ \mu g/m^3 < PM_{10,t+24h}$ concentration $\leq 150\ \mu g/m^3$ (Block 2) | | | | |
| | RMSE | 27.2372 | 28.9145 | 30.6125 |
| | MAE | 22.0516 | 23.9327 | 24.5156 |
| | MAPE | 0.2997 | 0.3166 | 0.3309 |
| $PM_{10,t+24h}$ concentration $> 150\ \mu g/m^3$ (Block 3) | | | | |
| | RMSE | 106.0264 | 140.4993 | 131.3888 |
| | MAE | 83.4721 | 124.5067 | 108.5374 |
| | MAPE | 0.3668 | 0.5553 | 0.4747 |

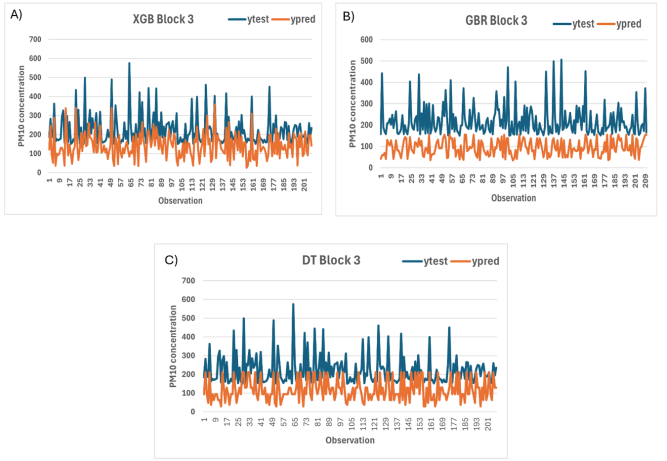


Fig. 5. Actual vs. Predicted for Block 3 of PM10 concentration for A) XGBoost B) GBR C) DT.

## IV. CONCLUSION

The primary contribution of this study is to focus on extreme values using machine learning methods. Additionally, the evaluation of ML models is further explored through data blocking to assess whether the skewed data can be effectively modelled using the same ML approach. Based on

TABLE VIII. PERFORMANCE RESULTS OF XGB, GBR AND DT MODEL FOR ALL AIR QUALITY DATA

| Model | Performance Indicator | Overall | $PM_{10,24h}$ concentration $\leq$ 50 µg/m$^3$ (Block 1) | 50 µg/m$^3$ < $PM_{10,24h}$ concentration $\leq$ 150 µg/m$^3$ (Block 2) | $PM_{10,24h}$ concentration > 150 µg/m$^3$ (Block 3) |
|---|---|---|---|---|---|
| **Extreme Gradient Boosting (XGB)** | RMSE | 21.5921 | 14.1875 | 27.2372 | 106.0264 |
| | MAE | 14.2396 | 10.6636 | 22.0516 | 83.4721 |
| | MAPE | 0.4816 | 0.5400 | 0.2997 | 0.3668 |
| | N | 16488 | 12427 | 3855 | 208 |
| **Gradient Boosting Regression (GBR)** | RMSE | 24.5051 | 14.1673 | 28.9145 | 140.4993 |
| | MAE | 15.7770 | 11.3487 | 23.9327 | 124.5067 |
| | MAPE | 0.5528 | 0.7274 | 0.3166 | 0.5553 |
| | N | 16488 | 12367 | 3912 | 211 |
| **Decision Tree (DT)** | RMSE | 24.7156 | 15.2412 | 30.6125 | 131.38885 |
| | MAE | 15.5915 | 11.2781 | 24.5156 | 108.5374 |
| | MAPE | 0.5164 | 0.5751 | 0.3309 | 0.4747 |
| | N | 16488 | 12427 | 3855 | 208 |

the discussion of all comparisons between the overall data and the blocks (as discussed above), XGBoost outperforms the other two models with RMSE(21.5921), MAE(14.2396) and MAPE(0.4816), indicating XGB model is more efficient for predicting $PM_{10}$ concentration. The comparison Block 1, Block 2, and Block 3 air quality data blocks show a decline in performance, as indicated by RMSE, MAE, and MAPE. The performance gap is significantly larger for the Block 3 air quality block compared to the overall, Block 1, Block 2 air quality blocks. This disparity arises from the presence of extreme values in the Block 3 air quality block, making it as challenging for the model to generate accurate predictions. As a result, the error indicators become significantly high, leading to a high discrepancy between actual and predicted $PM_{10}$ concentrations. For further analysis, since XGBoost outperforms the other models, it will be further utilized and enhanced to better handle extreme data, as this is essential for improving $PM_{10}$ concentration predictions, particularly during haze events with elevated $PM_{10}$ levels.

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# Towards Hybrid Meta-Heuristic Analysis for the Optimization of Fundamental Performance in Robotic Systems

Boudour Dabbaghi[1], Faiçal Hamidi[2], Mohamed Aoun[3], Houssem Jerbi[4]
Research Laboratory MACS LR16ES22, University of Gabes, Gabes, Tunisia[1,2,3]
Laboratory of Information-Communication and Knowledge Sciences and Techniques,
University of Western Brittany, Lorient, France[2]
Department of Industrial Engineering-College of Engineering,
University of Hail, Hail 1234, Saudi Arabia[4]

***Abstract*—This paper examines the concept of implementing a hybrid optimization approach through combining analytical and meta-heuristic approaches to improve the performance of practical engineering systems. Designed in support of artificial intelligence strategy, the proposed approach ensures high stability and efficiency under actuators saturation constraint. This is a well-known and sensitive problem in robotics and control. Specifically, this paper deals with the problem of computing the stability region for controlled systems. While addressing this issue, research approaches take into consideration the fact that actuator saturation may occur. It is imperative to maintain this propriety and ensure the reliability of design control systems, particularly those developed to control robot actuators. Models of the studied systems are based on differential algebraic representations and polytypic regions in state space. The developed technique combines LMI with an improved meta-heuristic based optimization approach that fast searches and enlarge domains of attraction for robot actuators. The direct Lyapunov theory is used to analyze and validate stability key performance. A numerical example study has been conducted to validate the proposed approach's efficacy and efficiency. A comparative benchmarking study has been carried out to highlight the main concepts and results of this study.**

***Keywords*—Domain of Attraction (DA); Differential Algebraic Representation (DAR); meta-heuristic approach; actuators saturation***

## I. Introduction

### A. Motivation

In robotic systems, actuators saturation is a problem that requires careful consideration. Under faulty conditions, and/or model uncertainties, robots may be more likely to experience this problem, and its solution becomes more difficult. Among reliable robots examined are general architectures, spatial robots, and robots with parallel or serial architectures. As part of the control techniques, a model reference process is implemented as well as an estimated torque approach in the feed-forward approach [1].

Furthermore, the feedback process involves conventional controllers. In the context of stability assurance, these methods rescue the robot from unstable dynamics by considering actuator saturation during the design phase [2]. Previous studies indicate that the time regulation method coupled with basin of attraction enlargement techniques are suitable for robots control methods. Besides addressing totally failed actuator joints, these methods also provide solutions for partial defects of various actuator joints [3].

For a class of nonholonomic mobile robots, a saturated trajectory tracking control design is presented in study [1]. A bounded dynamic continuous feedback controller is developed to ensure finite-time kinematic convergence. Saturation constraints related to attraction domains as well as errors associated with tracking initial values are considered. In control systems theory, attraction domains provide a useful means of analyzing the consequences of system actuator input saturation [3]. Sets such as these identify the system initial conditions under which the control technique results in attraction to stable equilibrium points [3]. Describes these sets in the context of an exponentially unstable open-loop plant. A single actuator controls such a model that is characterized by actuator saturation and modeling time delay characteristics. Consequently, approaches to estimating attraction domains are relevant for robot control design theory since these approaches provide sufficient, and necessary conditions for attractivity.

Equally significant, these approaches allow the identification of operational stability sets in which system actuators can perform in a non-saturated state.

### B. Fundamental Context

In general, in the real world, all physical control systems are inherently nonlinear: so, it is difficult to develop an analytical technique that can be applied to any nonlinear system [4]. In almost all physical control, the presence of an input saturation has been identified practically and this occurrence of saturation could result in nonlinear phenomena [4], [5], [10]. This has garnered a lot of interest to conduct numerous studies focusing on the modeling as well as assessment of its impact on the global stability and dynamical performance pertaining to closed-loop controlled systems. The results of most of these studies have accounted for the restricted class of linear open-loop systems. In such a particular case, even when the closed-loop controlled system is deemed to be linear locally , the nonlinearity could result in degradation of their performance or lead to instability. Thus, numerous analysis techniques were regarded to assess the DA pertaining to linear models

subject to a control input saturation constraint. Many works can describe the saturation of inputs in different representations for the sake of facilitating stability analysis. However, a good approach would be employing the generalized sector condition pertaining to dead zone nonlinearities. Furthermore, a key part of stability analysis is the representation of the system. Dynamic nonlinear systems can be represented in a variety of ways in the literature. As a consequence, commonly used the Differential Algebraic Representations (DAR) modeling indicates that the system offers results which are conservative than the Linear Fractional Representation(LFR), as well as the Linear Parameter Varying (LPV) forms thereof. A few notable representation systems are the LPV [6], the LFR [7], [8] and the DAR. The introduction of free multipliers to the studied system may be an effective approach to decreasing this late latent conservativeness. In this way, there would be less reliance on selecting control system matrices, as suggested by [6], taking advantage of different approaches. With regards to the framework pertaining to this problem, Coutinho, Trofino and co-workers [2], [9], [10], [11], [12], [56] put forward the Differential Algebraic Representations (DAR) to enable stability analysis, deal with control synthesis problems and employ to achieve tractable stability condition as linear matrix inequalities (LMI)[10]. The authors in [2] showed that DAR results in less conservative estimates pertaining to the region of attraction. DA signifies those initial conditions in which the system state converges with that of the equilibrium in an asymptotic manner. Numerous analysis techniques have been put forward for the estimation of the DA pertaining to linear models subject to input actuators saturation constraints. Different methods have been put forward to enable calculation of inner estimates for instance, approaches such as the La Salle method [13], Zubov method [14] and the trajectory reversing. In most situations, the DA estimation problem has been segregated to non-convex or convex optimisation problems for simplification [15], [16]. This has been dealt with by employing optimisation techniques such as SOS [17], [18], intelligent optimisation techniques [18],[19],[20] LMI [21], integration of the genetic as well as LMI. There are some other techniques to generate Lyapunov: for example, in [22] we proposed numerical techniques that define rational and quadratic Lyapunov functions based on Carleman linearization that permits the computation of the developed DA.

Generally in the literature estimating the domain of attraction is a complex problem. Some famous technique analysis stabilities are Lyapunov and Non-Lyapunov methodologies. The first family, described based on the Lyapunov function, set level associated in the region when a negative sign is included in its time derivative, which can be explained by a mathematical translation pertaining to an elementary observation: when a system's total energy lowers with time, then this system (linear or nonlinear, stationary, or not) tries to revert to an equilibrium state.

Generally, the literature indicates that the Lyapunov theory-based techniques are widely used to estimate the DA [23],[24],[25],[26],[27]. Linear Matrix Inequalities (LMI) optimization was employed by Coutinho et al. To estimate the domain of attraction for dynamic systems by considering the sets of levels of Lyapunov functions [28],[29]. The Largest Approximation of the DoA (LADoA) can be defined based on a Lyapunov Function (LF) for which the local asymptotic stability pertaining to the equilibrium point can be satisfied, characterized by a certain shape, by the LF itself. In such a case, the selection of the LF could significantly impact the conservativeness pertaining to the estimated domain.

### C. Literature Review

This study aimed to develop a method for determining the largest approximation DA pertaining to stable equilibrium's by investigating the maximal LFs. The main idea is to identify the best peaks providing an optimal region. The determination of the largest estimation of the DOA via the lyapunov function can be approached by serval method.[55] genetic algorithm will be implemented to adjust the coefficients of lyapunov function and control parameters, in [54] the article aims to develop an original numerical algorithm to construct a polynomial lyapunov function and maximizing domain of attraction using PSO algorithm. With this in mind, a great deal of research has focused on the integration of metaheuristic algorithms as an optimization tool to broaden the domain of attraction. It therefore seems appropriate to provide an overview of the main families of metaheuristic algorithms that can be used in this context. Many problems of optimization can be classified in these categories; Analytic or deterministic; heuristic or random: multi-objective or single objective[16], [30]. As well as we can classify these algorithms, two main classes can be identified: Meta heuristic and gradient. The first class are nature-inspired, and as they have been developed, based on some abstraction of nature. The second class is based on the gradient calculation theory; this class is very complex and risks peeling. In this work, we are interested in the meta heuristic algorithms as they are easy to manipulate and very efficient global search algorithms. Since then, many meta-heuristic nature-inspirited techniques have been developed: the particle swarm optimization (PSO)[49] is an algorithm designed to minic the foraging behavior of brids. Evolutionary strategy (ES)[31], firefly algorithm (FA) [32], ant colony optimization (ACO)[33], differential evolution (DE) [34], probability-based incremental learning (PBIL) [35], big bang–big crunch algorithm [36], bio-geography-based optimization (BBO) [36], harmony search (HS) [37], animal migration optimization (AMO) [38], krill herd method (KH) [39], [40], bat algorithm (BA) [41], teaching learning-based optimization (TLBO) [42], dragonfly algorithm (DA) [43], the Secretary Brid Optimization Algorithm(SBOA) [53]. (SBOA) is an innovative population based meta-heuristic approach such that is inspired from the survival behaviours of secretary brids in their natural habitat. the implementation of SBOA is structured into phases: an exploration step simulating a hunting strategy and an exploitation step simulating a escape strategy. In this work, we are interested by the secretary bird optimization algorithm. The SBOA algorithm offers advantages due to its simplicity showcasing its robustness and wide applicability.

This study employs the secretary birds optimization algorithm (SBOA) to assess the optimal value pertaining to the vertices for optimal domain of attraction (DA) estimation. SBOA is expected to offer higher performance versus the techniques suggested in [2],[12]. This paper aims to ameliorate the technique analyzed in [2] by combining the LMI with SBOA.

The paper is structured as follows: statement problem

preliminaries are introduced in Section II, and estimation DA using DAR representation in Section III. In this we further detail the DAR representation and signify the candidate Lyapunov and LMI formulation. In Section IV, we present the Secretary Brids Optimization algorithm implementation. Section V, is reserved for a numerical analysis study. Section VI introduce the discussion of the results, while Section VII ends the paper.

## II. Problem Statement and Preliminaries

Given a nonlinear affine systems described by:

$$\begin{cases} \dot{x} = f(x) + g(x)\, sat(u) \\ u = Kx \end{cases} \tag{1}$$

where, $x \in \Re^n$ represents the state variables vector, $u \in \Re$ signifies the control variable, with, $K \in \Re^{1\times n}$can be defined as the assumed constant vector denoting an input gain vector that relies linearly on the system state variables. $f(x), g(x) : \Re^n \to \Re^n$ defines a vectors of a nonlinear value function that satisfies the constraints pertaining to the uniqueness and existence of solution for all $x \in D_x$ and the equilibrium point of interest is the origin. A classical unitary saturation function is defined as follows [2]:

$$sat(u) := sign(u) \min\{|u|, 1\} \tag{2}$$

Analysis of the stability of the system (1) can employ Lyapunov theory [47]. **Lemma** [2]

Assume $V(x)$ to be a Lyapunov function pertaining to the system as Eq. (1) in the following region:

$$J = \{x : V(x) \leq 1\} \tag{3}$$

Should $\dot{V}(x)$ be negative, then may be defined as:

$$\dot{V}(x) = \frac{dV(x)}{dt} f(x) \tag{4}$$

The system seemed to be asymptotically stable and for all $x(0) \in J$ the trajectory $x(t)$ corresponds to $J$ while approaching the origin as $t \to \infty$. $\xi(x)$

### A. Determining a LF Candidate

This section is dedicated to introduce fundamental outcomes of the Lyapunov theory. Consider the following function:

$$V(x) = \xi(x)^T P \xi(x) \tag{5}$$

where, $\xi(x) \in \Re^{n_\xi}$ represents a rational vector function pertaining to $x$ and $P = P^T \in \Re^{n_\xi \times n_\xi}$ signifies the constant matrix that must be computed. The time derivate pertaining to $V(x)$ has been represented as follows: $\frac{dV(x)}{dt} = \dot{\xi}^T(x) P \xi(x) + \xi^T(x) P \dot{\xi}(x)$. It needs to be noted that $\xi(x)$ and $\dot{\xi}(x)$ denote the rational vector function pertaining to $x$ and $\dot{x}$.

*Remark:* The Lyapunov function has been presented in [13], which covers a broad class of physical process, including:

- Quadratic LF [8] where; $\xi(x) = x$.
- Bi-quadratic LF [28] and polynomial [29], where $\xi(x)$ being a polynomial vector function in $x$.
- Rational LF where $\xi(x)$ being a non-singular rational function of $x$ .

As a generally accepted rule, the more complex this vector is, the more conservative the results obtained. Hereafter we assume there exist DAR of $\xi(x)$ and $\dot{\xi}(x)$ defined as follows [2]:

$$\begin{cases} \xi(x) = E_1 x + E_2 \varsigma(x) \\ 0 = \Gamma_1(x) x + \Gamma_2(x) \varsigma(x) \end{cases} \tag{6}$$

$$\begin{cases} \dot{\xi}(x) = F_1 x + F_2 \chi(x, \dot{x}) \\ 0 = \phi_1(x)\dot{x} + \phi_2(x)\chi(x, \dot{x}) \end{cases} \tag{7}$$

where, $\varsigma(x) \in \Re^{n_\varsigma}, \chi(x, \dot{x}) \in \Re^{n_\chi}$ are nonlinear vector functions, $E_1 \in \Re^{n_\xi \times n}, E_2 \in \Re^{n_\xi \times n_\varsigma}, F_1 \in \Re^{n_\xi \times n}, F_2 \in \Re^{n_\xi \times n_\chi}$ are constant matrices, $\Gamma_1(x) \in \Re^{n_\phi \times n}, \Gamma_2(x) \in \Re^{n_\phi \times n_\varsigma}, \phi_1(x) \in \Re^{n_\phi \times n}, \phi_2(x) \in \Re^{n_\phi \times n_\chi}$ are affine matrix functions of $x$. The representation is called well defined if the following hypotheses satisfied: $\Gamma_2(x), \phi_2(x)$ have full column-rank for all $x \in D_x$.
Using Eq. (6) and Eq. (7) it comes,

$$V(x) = \begin{bmatrix} x \\ \varsigma(x) \end{bmatrix}^T \Delta P \begin{bmatrix} x \\ \varsigma(x) \end{bmatrix} \tag{8}$$

$$\begin{aligned} \dot{V}(x) &= \begin{bmatrix} \dot{x} \\ \dot{\varsigma}(x) \end{bmatrix}^T \Delta P \begin{bmatrix} x \\ \varsigma(x) \end{bmatrix} + \begin{bmatrix} x \\ \varsigma(x) \end{bmatrix}^T \Delta P \begin{bmatrix} \dot{x} \\ \dot{\varsigma}(x) \end{bmatrix} \\ &= 2 \begin{bmatrix} x \\ \varsigma(x) \end{bmatrix}^T \Psi P \begin{bmatrix} \dot{x} \\ \chi(x, \dot{x}) \end{bmatrix} \end{aligned} \tag{9}$$

with, $\Delta P = \begin{bmatrix} E_1^T P E_1 & E_1^T P E_2 \\ E_2^T P E_1 & E_2^T P E_2 \end{bmatrix}$,

$\Psi P = \begin{bmatrix} E_1^T P F_1 & E_1^T P F_2 \\ E_2^T P F_1 & E_2^T P F_2 \end{bmatrix}$

### B. Domain of Attraction

Domain of attraction (DA) can be described as those initial conditions in which the states converge towards equilibrium asymptotically [44], [46], [45]. According to the Lyapunov function introduced in the Section II-A we can estimate the domain of attraction. A region of attraction is given as follows;

$$J = \left\{ x \in D_x : \xi(x)^T P \xi(x) \leq 1 \right\} \tag{10}$$

where, $P \in \Re^{n\times n}$ is a positive definite matrix and $J$ is the normalised ellipsoid. When the condition $\dot{V}(x)$ hold for all $x(0) \in J$, the region $J$ can be represent an estimated domain of attraction for system (1), this means that any trajectory starting within $J$ will converge to the origin, without exiting $J$.

### C. Statement of the Generalized Sector-Based Constraint

Consider $H \in \Re^{1\times n}$ the row vector function and define the set below:

$$S = \{x \in \Re^n; |(K-H)x| \leq 1\} \tag{11}$$

when $x$ belongs to $S$, the relation can be stated as [5], then the deadzone nonlinearity $\psi(Kx)$ meets the following inequality which is valid for any positive scalar $\mu$.

$$\psi(Kx)^T \mu \left[\psi(Kx) - Hx\right] \leq 0 \tag{12}$$

Let the set $J$ and $S$ defined respectively in (10) and (11) and consider a matrix $C(x) \in \Re^{n_c\times(n+n_\xi)}$ affine in x, where $C(x)\left[\begin{array}{cc} x & \varsigma(x)\end{array}\right] = 0$. Let $S$ included in $J$. If a matrix $\Xi$ exists the following condition is satisfied:

$$\left[\begin{array}{cc} 1 & \left[\begin{array}{cc}(K-H) & 0\end{array}\right] \\ \left[\begin{array}{c} K^T - H^T \\ 0\end{array}\right] & \left(\sum(P) + NC(x) + C(x)^T N^T\right)\end{array}\right] \geq 0 \tag{13}$$

### D. Polytope in State Space

Let $D_x$ is given polytope (with $n_e$ vertices), which defines the intiales conditions and contains the origin. Therefore, the polytope can be defined as follows:

$$D_x = \left\{x \in \Re^n : a_i^T x \leq 1, i = 1, ....., n_e\right\} \tag{14}$$

with, the constant vectors $a_i \in \Re^n$ are defined such that $a_i^T x = 1$ for all groups of adjacent vertices.
Similarly, to the result of section II-C the set $J$ include in $D_x$ and a matrix $C(x)\left[\begin{array}{cc} x & \varsigma(x)\end{array}\right] = 0$, if the following condition is satisfied:

$$\begin{array}{l}\left[\begin{array}{cc} 1 & \left[\begin{array}{cc}-a_i^T & 0\end{array}\right] \\ \left[\begin{array}{c} -a_i \\ 0\end{array}\right] & \left(\Sigma(P) + RC(x) + C(x)^T R^T\right)\end{array}\right] \geq 0, \\ \forall k \in \{1, \ldots, n_e\}\end{array} \tag{15}$$

## III. Estimation of the Domain of Attraction using DAR Representation

### A. Differential Algebraic Representation DAR

Set the nonlinearity of the following dead zone [48]

$$\psi(u) = u - sat(u) \tag{16}$$

A nonlinear dead-zone $\psi(u)$ is defined in this work to justify the occurrence of the saturation nonlinearity. Taken into accounts, Eq. (16) the system Eq. (1) is presented as follows:

$$\left\{\begin{array}{l}\dot{x} = f(x) + g(x)u - g(x)\psi(u) \\ u = Kx\end{array}\right. \tag{17}$$

A nonlinear system can be described in many different representation. In this case, the system is represented by the differential algebraic representation (DAR). That is defined as follows:

$$\left\{\begin{array}{l}\dot{x} = A_1 x + A_2 z(x) + A_3 sat(Kx) \\ 0 = \pi_1 x + \pi_2 z(x) + \pi_3 sat(Kx)\end{array}\right. \tag{18}$$

where $z \in \Re^{n_z}$ signifies a nonlinear auxiliary vector pertaining to $x$, which includes the nonlinear elements in $f(x)$. $A_1 \in \Re^{n\times n}$, $A_2 \in \Re^{n\times n_z}$ and $A_3 \in \Re^{n\times 1}$ can be defined as constant matrices, and $\pi_1 \in \Re^{n_z\times n}$,$\pi_2 \in \Re^{n_z\times n_z}$,$\pi_3 \in \Re^{n_z\times n}$ represent the affine matrix functions pertaining to $x$. To ensure the differential algebraic representation is well determined and the solution $x$ is unique, the previous assumptions have been implemented. If $z$ is invisible, considering Eq. (18) we have that:

$$z(x) = -\pi_2^{-1}\left(\pi_1 x + \pi_3 sat(u)\right) \tag{19}$$

System (1) can be expressed as follows:

$$\dot{x} = (A_1 - A_2\pi_2^{-1}\pi_1)x + (A_3 - A_2\pi_2^{-1}\pi_3)sat(u) \tag{20}$$

As a result, the term $sat(u)$ can be substituted with Eq. (16), so the system Eq. (1) can be expressed in the following form:

$$\left\{\begin{array}{l}\dot{x} = (A_1 + BK)x + A_2 z(x) - B\psi(Kx) \\ 0 = (\pi_1 + \pi_3 K)x + \pi_2 z(x) - \pi_3\psi(Kx)\end{array}\right. \tag{21}$$

with, $B = A_3 \in \Re^{n\times 1}$.

### B. LMI Formulation

In this part of the study, we made a proposition for LMI condition development to ensure the Lypaunov function presented in Eq. (8). This LMI is attained by integrating the linear annihilator condition [10] and Finsler's lemma [47]. Thus, it is possible to define the solution of estimating the area of attraction with respect to LMIs that are state dependent as shown in the theorem given below.

For the system represented in Eq. (21), the Lypaunov function in Eq. (8) and its time derivative in Eq. (9) are considered first with, $\nu = \left[\begin{array}{cccc}\xi & \varphi & z & \psi(Kx)\end{array}\right]$

Than it comes:

$$\begin{array}{l}\frac{dV(x)}{dt} = \\ \left[\begin{array}{c}\xi \\ \varphi \\ z \\ \psi(Kx)\end{array}\right]\left[\begin{array}{cccc} 0 & \Psi P & 0 & 0 \\ \Psi P^T & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0\end{array}\right]\left[\begin{array}{c}\xi \\ \varphi \\ z \\ \psi(Kx)\end{array}\right]^T < 0\end{array} \tag{22}$$

According to the Section II-C if the relation in Eq. (12) is verified for any positive scalar such that

$$\frac{dV(x)}{dt} - 2\psi(Kx)^T \mu(\psi(Kx) - Qx) < 0 \tag{23}$$

Therefore (23) can be written as follows

$$\nu^T \Lambda \nu < 0 \tag{24}$$

$$\text{with, } \Lambda = \begin{bmatrix} 0 & \Psi P & 0 & \begin{bmatrix} \mu H^T \\ 0 \end{bmatrix} \\ \Psi P^T & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \begin{bmatrix} \mu H & 0 \end{bmatrix} & 0 & 0 & -\mu \end{bmatrix}$$

by exploiting the DAR's property of equality in Eq. (21), Eq. (6), Eq. (7) and the linear annihilator obtained by the formula [10] can be utilized to obtain that

$$\begin{bmatrix} L(x) & 0 & 0 & 0 \\ \Gamma_1(x) & \Gamma_2(x) & 0 & 0 \\ 0 & 0 & \phi_1(x) & \phi_2(x) \\ A_{cl} & 0 & -\mathrm{I}_n & 0 \\ \pi_1(x) + K\pi_3(x) & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ A_2 & -B \\ \pi_2(x) & \pi_3(x) \end{bmatrix} \begin{bmatrix} x \\ \varsigma(x) \\ \dot{x} \\ \chi(x, \dot{x}) \\ z \\ \psi(x) \end{bmatrix} = 0 \tag{25}$$

with, $A_{cl} = A_1 + BK$.

Using the Finsler's lemma[47] for Eq. (24), Eq. (25) such that:

$$\begin{bmatrix} 0 & \Psi P & 0 & \begin{bmatrix} \mu H^T \\ 0 \end{bmatrix} \\ \Psi P^T & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \begin{bmatrix} \mu H & 0 \end{bmatrix} & 0 & 0 & -\mu \end{bmatrix} + \tag{26}$$

$$MX(x) + X^T(x) M^T < 0,$$

$$\text{with, } L(x) = \begin{bmatrix} x_2 & -x_1 & 0 & \cdots & 0 \\ 0 & x_3 & -x_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & x_n & -x_{(n-1)} \end{bmatrix},$$

$$C(x) = \begin{bmatrix} L(x) & 0 \\ \Gamma_1(x) & \Gamma_2(x) \end{bmatrix}$$

**Theorem 1**

Consider the nonlinear system with saturating actuators given in Eq. (1) with $u(t) = Kx(t)$ and let $\xi(x)$ be a rational vector function in terms of $x$ with DAR of $\xi(x)$ and $\dot{\xi}(x)$ as given in Eq. (6) and Eq. (7) and lets define a polytope $D_x$. If there exists matrices $P = P^T, H, R, N, M$ and $\Upsilon$, of appropriate dimensions that satisfy the following LMIs for all $x \in \Theta(D_x)$. For instance, the following LMIs can be represented:

$$\Delta P + \Upsilon C(x) + C(x)^T \Upsilon^T > 0 \tag{27}$$

$$\begin{bmatrix} 1 & \begin{bmatrix} -a_i^T & 0 \end{bmatrix} \\ \begin{bmatrix} -a_i \\ 0 \end{bmatrix} & \Delta P + RC(x) + C^T(x) R^T \end{bmatrix} \geq 0 \tag{28}$$

$$\begin{bmatrix} 1 & \begin{bmatrix} K - H & 0 \end{bmatrix} \\ \begin{bmatrix} K^T - H^T \\ 0 \end{bmatrix} & \Delta P + NC(x) + C^T(x) N^T \end{bmatrix} \geq 0 \tag{29}$$

$$\begin{bmatrix} 0 & \psi P & 0 & \begin{bmatrix} H^T \mu \\ 0 \end{bmatrix} \\ \psi P & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \begin{bmatrix} H\mu & 0 \end{bmatrix} & 0 & 0 & -\mu \end{bmatrix} + MX(x) + \tag{30}$$

$$\mathrm{X}^T(x) M^T < 0$$

So, for all $x(0) \in J$, trajectory $x(t)$ belongs to $J$ and $V(x) = \xi(x)^T P \xi(x)$ in Eq. (5) is a Lyapunov function in $D_x$. Theorem 1 establishes a sufficient condition to guarantee that an $J$ formed by a Lyapunov function, is an domain of asymptotic stability for the closed loop system. Also, let try to find a domain estimate as large as possible. Therefore, the idea is to select among all possible feasible solutions for LMI in Eq. (27)-(30) the one that offers the largest possible set $J$, taking into account a volume size criterion. In the more general case described here, where the domain of attraction is an ellipsoid, a solution to the volume maximization problem can be directly addressed through the following optimization problem:

$$\begin{cases} Max\,(Vol) = \frac{1}{trace(P)} \\ subject\ to: (27) - (30) \end{cases} \tag{31}$$

The domain of attraction volume maximization cannot exist when parameters introduced in LMI are not well chosen. For example if we leave $\mu$ free, or badly chosen we lose the convexity of the conditions of Theorem 1 and consequently LMI does not give solutions from where it will not be feasible. On the other hand, the polytope search of admissible states gives the largest domain of the state space $D_x(a_1, a_2)$ so that the system is stable by solving Eq. (27-30), for an optimal pair $(a_1, a_2)$. In the end the attraction domain search will be bounded in the admission polytope by selecting the optimal Lyapunov function.

## IV. Main Results

In this section we develop an algorithm to expand the domain of attraction using the SBOA-based meta-heuristic method. This section introduces a strategy for selecting the right parameter $\mu$ to guarantee the convexity of theorem 1, the best pair $(a_1, a_2)$ to maximize the admissible polytope of the states and the right choice of the optimal Lyapunov function matrix $P$. Evalutionary tehniques are emloyed to determine the parameters $\mu$, and the coefficients of the Lyapunov function. The form of the candidate Lyapunov function defined by the user, and its corresponding domain are validated for and the LMIs of theorem 1, are feasible. In case these conditions are not met and the LMIs are not feasible, we repeatedly estimate the parameters in question and the coefficients of the Lyapunov function until the LMI optimization has a solution. The basis of this criterion is to obtain optimal parameters through the use of evolutionary algorithms.

### A. Proposed Method to Enlarging DA

*1) Secretary Birds Optimization Algorithm:* Secretary birds [53] are large, terrestrial birds of prey that generally found in tropical savannas or semi-desert regions. Secretary birds are perdators of snakes on the Arican continent including species like the black mamba and Cobra. The SBOA algorithm derives inpiration from the survival techniques of searching or prey and escaping tough ecologies. A secretary birds optimisation algorithm is created to handle complex optimisation challenges. The secretary brid's itelligence is showcased in its strategies for evading predators. The SBOA is composed of the following parts:

**Initiation Phase:** The first step in solving a typical minimization problem $f(x)$ is to determine the initial solutions that will be used to initiate the search. In the population, each individual represents a solution to the optimization problem and this solution is initialized according to the following equation:

$$X_j = lb + r \times (ub - lb), j = 1, 2, \ldots, N \tag{32}$$

where, $X_j$ is the postion of the $j^{th}$ $lb$ and $ub$ are the lower and upper bounds. $rand$ designates a random number in $[0, 1]$. $N$ is the dimension of the problem. In addition, the fitness value of the solution $X_i$ denoted as $F_i = f(X_i)$ is a measure of its quality.

**Hunting Strategy of Secretary Birds (Exploration step):** Contraty to the other fierce predators secretay birds employ a more intelligent strategy for hunting snakes. Therefore, the whole hunting process can be broken down into three steps, they include searching prey, consuming prey, and attacking prey.

- Searching prey: In this stage, secretary birds need seek prey while keeping a safe range. By referencing the positions of the others two secretary birds, the secretary brid can scout new potential areas. For this reason, the differential mutation operations are incoperated to maintain algorithm diversity. The position of each individual $X_i$ is updated using equations (33) and (34) when the current iteration time $t$ is smaller than one-third of the maximum iterations $T$.

$$X_t^{newP}(t) = X_t(t) + (X_{random_1}(t) - X_{random_2}(t)) \times R_1 \tag{33}$$

$$\begin{cases} X_t(t+1) = X_t^{newP}(t), & if \quad F_t^{newP} < F_i \\ X_t(t+1) = X_t(t), else \end{cases} \tag{34}$$

  Where, $R_1$ is a random vector consisting of $1 \times M$ elements chosen randoml from $[0, 1]$. $X_{random_1}, X_{random_2}$ represent two individuals randomly chosen from the present population.

- Consuming prey: When secretary brids identify potential prey their first action is to hover around the snake exhibiting aile footwork and maneuvers. Through observing and baiting opponents while circling, the prey's patience will be exhausted, causing it to lower its guard. Considering the current best individual as the prey, other secretary birds adjust their positions to move closer to it. In this stage, we use Brownian motion (RB) to simulate a random movement of the secretary birds such that is given by:

$$RB = randn(1, D) \tag{35}$$

  Hence, updating the secretary birds position during the consuming pery stage can be represented as follows:

$$X_t^{newP}(t) = X_{best}(t) + e^{\left(\frac{t}{T}\right)^4} \times (RB - 0.5) \times (X_{best}(t) - X_t(t)) \tag{36}$$

$$\begin{cases} X_t(t+1) = X_t^{newP}(t), & if \quad F_t^{newP} < F_t \\ X_t(t+1) = X_t(t), else \end{cases} \tag{37}$$

  where, $X_{best}$ represent the best solution for the current population.

- Attacking prey: When, the prey well exhausted, so it the time to start the attack. Here the secretary brid used the Levy flight approach. Therefore, the characteristics of this stage are describe by the following Eq. (38), (39)

$$X_t^{newP}(t) = X_{best}(t) + \left(\left(1 - \frac{t}{T}\right)^{\frac{2 \times t}{T}}\right) \times X_t(t) \times RL \tag{38}$$

$$\begin{cases} X_t(t+1) = X_t^{newP}(t), if \quad F_t^{newP} < F_t \\ X_t(t+1) = X_t(t), else \end{cases} \tag{39}$$

  where $RL$ represents a random movement(the levy fight representation) which is defined as follows:

$$RL = 0.5 \times Levy(M) \tag{40}$$

**Escape Strategy for Secretary Birds (Exploitation step):** In nature the main enemies of secretary bird are large predators. Such as eagles, hawks, foxes, and jackals, which may attack them or steal their food. In this cas we proposed two categories:

- Camouflage based on environment: When secretary birds are confronted by enemies, their first strategy is to camouflage themselves in order to avoid danger. The secretary birds modify their positions around the prey (which represents the best individual) reflecting the behavior of attempting to evade local optimal algorithms. The following Eq. (41),(42) present the mathematical model of this approach.

$$\mathrm{X}_t^{newP}(t) = \mathrm{X}_{best}(t) + (2 \times RB - 1) \times \left(1 - \tfrac{t}{T}\right)^2 \times \mathrm{X}_t(t) \tag{41}$$

$$\begin{cases} X_t(t+1) = X_t^{newP}(t), if \quad F_t^{newP} < F_t \\ X_t(t+1) = X_t(t), else \end{cases} \tag{42}$$

  Where,$\left(1 - \frac{t}{T}\right)^2$ is a disturbance factor that helps to strike a balance between exploration (seeking new solutions) and exploitation (using known solutions).

- Running mode: Then in this step, if they can't avoid they enem we use the approach of flight or rapid running to maintain their saftey. Secretary brid updated their new position by using the following equation

$$X_t^{newP}(t) = X_{best}(t) + R_2 \times (X_{rand}(t) - K \times X_t(t)) \tag{43}$$

$$\begin{cases} X_t(t+1) = X_t^{newP}(t), if \quad F_t^{newP} < F_t \\ X_t(t+1) = X_t(t), else \end{cases} \tag{44}$$

In a SBOA, the main operation involves computing the fitness function. Therefore the quality of the particle is evaluated using its objective function, the goal being to maximize it.

$$v = \frac{1}{trace(P)} \tag{45}$$

To achieve this objective, a meta-heuristic technique is used. We developed a technique to expand the DA by integrating the SBO algorithm and an LMI technique to ensure the computing of the maximal LF defined in Eq. (4). In this work we estimate again by SBOA $\mu$ and the values of the vertices $a_1$ and $a_2$ to expand the domain of attraction defined by Eq. (10).

$$\begin{cases} Max(Vol(J)) = \frac{1}{trace(P)} \\ s.t: \begin{cases} \min \ \theta \\ s.t: LMI \ (27)-(30), \ a \quad feasible \quad solution \\ \theta - trace\left(\Delta P + \Upsilon C(x) + C(x)^T \Upsilon^T\right) > 0 \end{cases} \end{cases} \tag{46}$$

The designed approach is synthesized in the following flowchart depicted in the Fig. 1.

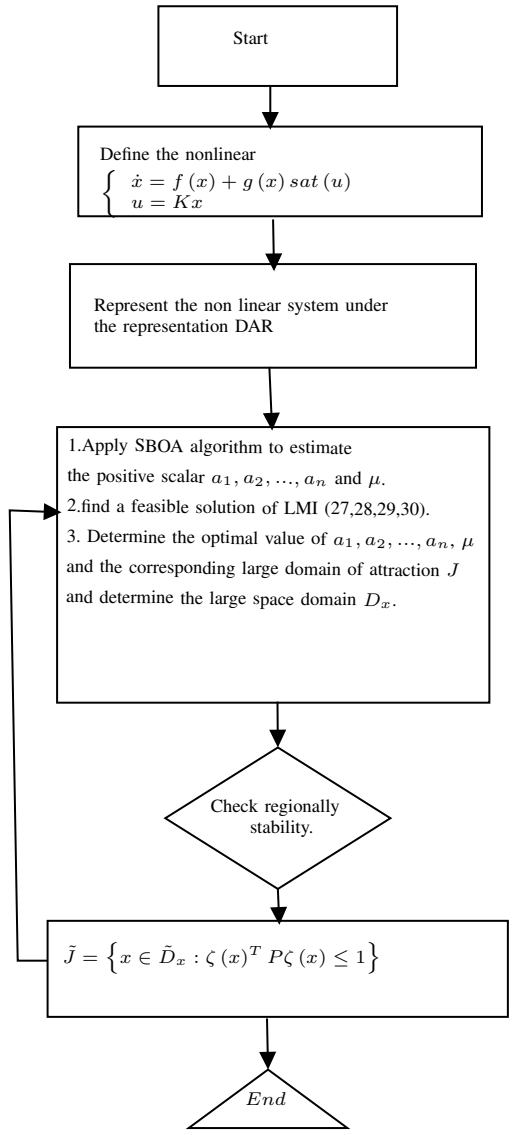


Fig. 1. Flowchart of the meta-heuristic technique for estimating the DA of a nonlinear system with input saturation.

## V. Numerical Examples

In this section, numerical examples are presented to verify the effectiveness of the proposed approach. The conditions introduced in this paper were implemented in MATLAB (R2015) using the parser Yalmip and the solver SDPT3.

*Example 1*

Consider a nonlinear system with saturated input given by [2]:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = (1+x_1^2)x_1 + (2+8x_2^2)x_2 + sat(u) \\ u = Kx \end{cases} \tag{47}$$

The state is $x = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T$ and the control input is $u(t) = -2x_1(t) - 4x_2(t)$. In this paper, we search for the Lyapunov function that stabilizes the system asymptotically, minimizes the cost function represented by the trace of Matrix P definite positive, and has the largest estimation of the DA of system (47) in a closed loop. We use the proposed method for example 1. Note that, $D_x(a_1, a_2) := \left\{x \in \Re^2 : |x_1| \leq a_1, |x_2| \leq a_2\right\}$ is a state admissible, with $a_1, a_2$ tow positive predefined scalars. First, we reformulate the system (47) in the DAR form. Then, by applying the equation (16)-(18), a DAR of this system is given by:

$$\begin{cases} \dot{x} = (A_1 + BK)x + A_2 z(x) - B\psi(Kx) \\ 0 = (\pi_1 + \pi_3 K)x + \pi_2 z(x) - \pi_3 \psi(Kx) \end{cases} \tag{48}$$

where, $z = \begin{bmatrix} x_1^2 & x_2^2 & x_1^3 & x_2^3 \end{bmatrix}^T$, $A_{cl} = A_1 + BK$, $A_3 = B$,

$$A_{cl} = \begin{bmatrix} 0 & 1 \\ -1 & -2 \end{bmatrix}, A_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 8 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 1 \end{bmatrix},$$

$$\pi_1 = \begin{bmatrix} x_1 & 0 \\ 0 & x_2 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \pi_2 = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ x_1 & 0 & -1 & 0 \\ 0 & x_2 & 0 & -1 \end{bmatrix}, \pi_3 = 0$$

As a means of evaluating the stability of the system, two distinctive Lyapunov functions are taken. First, the quadratic Lyapunov

function is analyzed:

$$V_1(x) = \xi_1^T(x) P_1 \xi_1(x) \tag{49}$$

Second a polynomial Lyapunov function is considered:

$$V_2(x) = \xi_2^T(x) P_2 \xi_2(x) \tag{50}$$

where $\xi_1(x) = x$, $\xi_2(x) = \begin{bmatrix} x_1^2 & x_1x_2 & x_2^2 & x_1 & x_2 \end{bmatrix}^T$. $P_1 \in \Re^{2\times 2}$ and $P_2 \in \Re^{5\times 5}$ are two symmetric matrices to be computed. The polynomial LF calculation requests the decomposition of $\xi_2(x)$ and $\dot{\xi}_2(x)$ as stated below.

$$\begin{cases} \xi_2(x) = E_1 x + E_2 \varsigma(x) \\ 0 = \Gamma_1(x)x + \Gamma_2 \varsigma(x) \\ \dot{\xi}_2(x) = F_1 \dot{x} + F_2 \chi(x,\dot{x}) \\ 0 = \phi_1(x)\dot{x} + \phi_2 \chi(x,\dot{x}) \end{cases}, \tag{51}$$

where, $\varsigma(x) = \begin{bmatrix} x_1^2 & x_1x_2 & x_2^2 \end{bmatrix}^T$, $E_1 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$,

$$E_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \Gamma_1(x) = \begin{bmatrix} x_1 & 0 \\ 0 & x_1 \\ 0 & x_2 \end{bmatrix},$$

$$\Gamma_2 = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix}, \chi(x,\dot{x}) = \begin{bmatrix} x_1\dot{x}_2 \\ x_1\dot{x}_2 \\ x_2\dot{x}_1 \\ x_2\dot{x}_2 \end{bmatrix},$$

$$F_1 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, F_2 = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix},$$

$$\phi_1(x) = \begin{bmatrix} x_1 & 0 \\ 0 & x_1 \\ x_2 & 0 \\ 0 & x_2 \end{bmatrix}, \phi_2 = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}$$

the optimization problem (46) was solved to obtain the largest admissible polytope in state space and that maximizes the domain of attraction. The Fig. 2 shows the dynamic of the cost function. The optimal domain is obtained as:

$$\begin{cases} (a_1, a_2) = \begin{bmatrix} 0.51233 & 0.32322 \end{bmatrix} \\ P_{opt} = \begin{bmatrix} 4.6221 & 3.0714 \\ 3.0714 & 11.6130 \end{bmatrix}, \\ \theta = 16.2351 \end{cases} \tag{52}$$

Fig. 3 shows the evolution of the DA for the system Eq. (47) using SBOA approach. Fig. 4 represents the dynamic of the state space initialized from the tangency point state locus and the evolution of the input control of the system.

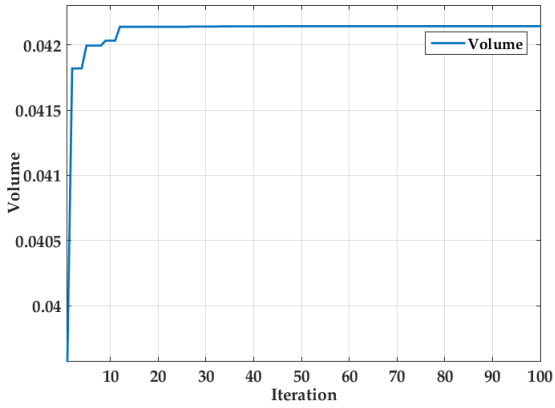


Fig. 2. Dynamic of the cost function using the SBOA approach for system (47) for obtain the optimal value of $\mu$.

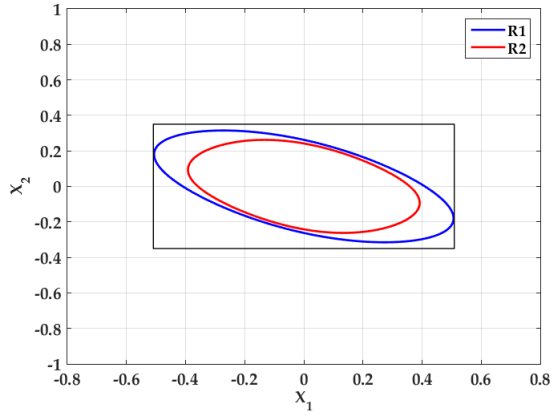


Fig. 3. Approximation of the DA for the system Eq. (47) using quadratic LF (Blue ellipsoid using SBOA technique - red ellipsoid analytical technique).

*Example 2*

Considering a single-link robot arm in [50]

$$\ddot{\theta}(t) = -\frac{Mgl}{J}\sin(\theta) - \frac{D}{J}\dot{\theta} + \frac{1}{J}u \tag{53}$$

where,

- $\theta$ is the angle position of the arm
- $u$ is the input control.
- $M$ is the mass of the poyload.
- $J$ is the moment of inertia.
- $g$ is the acceleration of gravity and $l$ is the length of the arm.

Assume, $x_1 = \theta, x_2 = \dot{\theta}$ then we obtain the following state space model of the robotic arm manipulator

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\frac{Mgl}{J}\sin(x_1) - \frac{D}{J}x_2 + \frac{1}{J}u \\ y = x \end{cases} \tag{54}$$

Then the values parameters for robotic arm are given by: $g = 9.81$, $l = 0.5$, for this work we consider the nominal value of $D =$

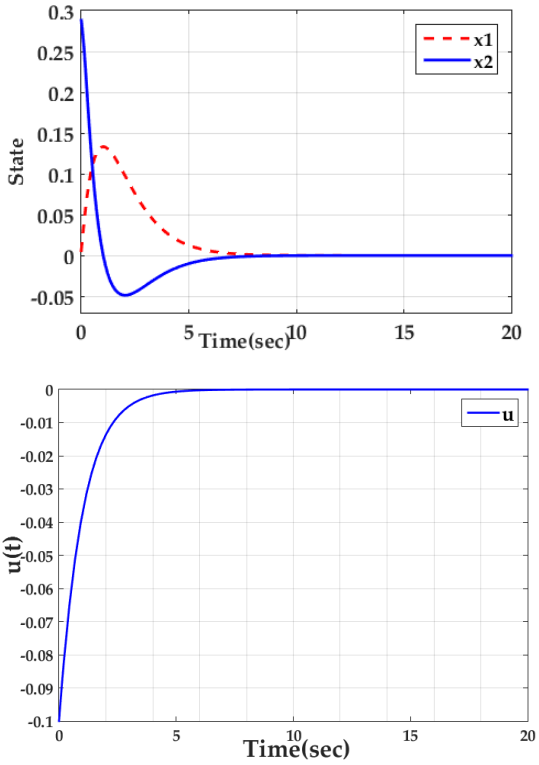


Fig. 4. Results of simulations for example 1: states dynamics and control input.

$D_0 = 2$ and for $J$ and $M$ we consider the mode 1 so $M = J = 1$, With this parameters chosen we obtain the following representation.

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -4.905 \times \sin(x_1) - 2 \times x_2 + u \\ y = x \end{cases} \tag{55}$$

Using the Taylor series $\text{atsin}(x) = x - \frac{x^3}{3!} + \frac{x^5}{5!} - \cdots$ then in this work we stop at $n = 3$ therefore $\sin(x) = x - \frac{x^3}{3!}$. Then, we obtain the following state-space:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -4.905 \times x_1 + \frac{4.905}{6} \times x_1^3 - 2 \times x_2 + u \\ y = x \end{cases} \tag{56}$$

This example cannot be applied with this approach because the absence of any indication for the command $u$. Where, $u = k_1 x_1 + k_2 x_2$ to find the parameters of the command $u$ we want to apply Chesi 2004 [51]. Therefore, we linearize in the vicinity of the equilibrium to establish a Lyapunov function LF:

$$A = \frac{\partial f}{\partial x}\bigg\|_{(0,0)} = \begin{bmatrix} 0 & 1 \\ -4.905 & -2 \end{bmatrix} \tag{57}$$

Then, for determine the matrix $P$ we used this equation: $A^T P + PA = -Q$ with $Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Such that, we obtain the following matrix $P$

$$P = \begin{bmatrix} 1.68 & 0.102 \\ 0.102 & 0.301 \end{bmatrix} \tag{58}$$

with $V(x) = 1.68x_1^2 + 0.204x_1x_2 + 0.301x_2^2$ and the controller class defined by $\phi(y) = y$,
$\Im = \left\{U = \begin{bmatrix} u_1 & u_2 \end{bmatrix} : u \in \begin{bmatrix} -1 & 1 \end{bmatrix}\right\}$. Let us examine the structure of the GEVP introduced in [51]. The degree of $\dot{V}$ denoted as $\delta_d$ is 4. As a result, $\delta_s$ can be chosen as follows: $\delta_s = 1$, so $m = 2$ and $x^{\{\delta_v\}} = x^{\{\delta_s\}} = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T, x^{\{m\}} = \begin{bmatrix} x_1x_2 x_1^2 x_1x_2 x_2^2 \end{bmatrix}^T$, it is found that

$$D_f(\alpha) = \begin{bmatrix} -1.0006 & -4 \times 10^{-4} & 0 & \alpha_1 & \alpha_2 \\ -4 \times 10^{-4} & -1 & -\alpha_1 & -\alpha_2 & 0 \\ 0 & -\alpha_1 & 0.2501 & 0.2460 & \alpha_3 \\ \alpha_1 & -\alpha_2 & 0.2460 & -2\alpha_3 & 0 \\ \alpha_2 & 0 & \alpha_3 & 0 & 0 \end{bmatrix},$$

$$D_g(U) = \begin{bmatrix} 0.204u_1 & 0.301u_1 + 0.102u_2 \\ 0.301u_1 + 0.102u_2 & 0.602u_2 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

In order to compute $W(S)$, let's note that $V = I_2$. Therefore, we have that $s = \begin{bmatrix} s_1 & s_2 \\ s_2 & s_3 \end{bmatrix}$,

$$K = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$W(S) = \begin{bmatrix} s_1 & s_2 & 0 & 0 & 0 \\ s_2 & s_3 & 0 & 0 & 0 \\ 0 & 0 & \tau s_1 & \tau s_2 & 0 \\ 0 & 0 & \tau s_2 & \tau(s_1 + s_3) & \tau s_2 \\ 0 & 0 & 0 & \tau s_2 & \tau s_3 \end{bmatrix}$$

$$W_2(S) = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1.68s_1 \\ 0 & 0 & 0.84s_2 + 0.102s_1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0.84s_2 + 0.102s_1 & 0 \\ 1.68s_3 + 0.408s_2 + 0.301s_1 & 0.102s_3 + 0.302s_2 \\ 0.102s_3 + 0.302s_2 & 0.301s_3 \end{bmatrix}$$

The obtained input control $u$ is given by: $u = -0.5043x_1 - 0.2863x_2$. In this step, we want to apply our proposal and given the DAR representation Eq. (21) with the auxiliary vector $z = x_1^2$, we consider

$A_1 = \begin{bmatrix} 0 & 1 \\ -5.4093 & -2.2863 \end{bmatrix}, A_2 = \begin{bmatrix} 0 \\ x_1 \end{bmatrix}, A_3 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \pi_1 = \begin{bmatrix} x_1 & 0 \end{bmatrix}, \pi_2 = -1$ and $\pi_3 = 0$.

To analyze the stability, we consider a quadratic Lyapunov function. SBOA is implemented with (maximum number of iterations 100 and the swarm size is 30). To obtain the optimal value of $\mu$, $(a_1, a_2)$. Fig. 5 present the evolution of the SBOA process for 100 iterations.

$$\begin{cases} (a_1, a_2) = \begin{bmatrix} 1.4221 & 2 \end{bmatrix} \\ P_{opt} = \begin{bmatrix} 0.6106 & 0.1142 \\ 0.1142 & 0.2714 \end{bmatrix} \\ \theta = 0.8819 \end{cases} \tag{59}$$

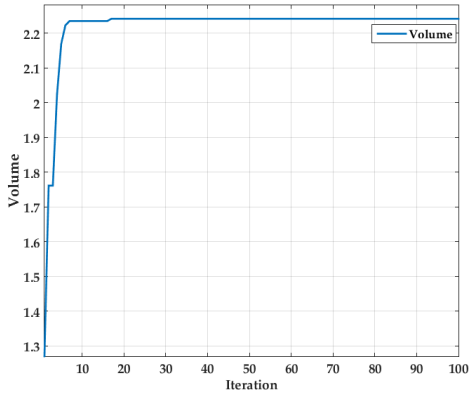


Fig. 5. Dynamic of cost function volume using the SBOA approach for nonlinear system to obtain the optimal value of $\mu$.

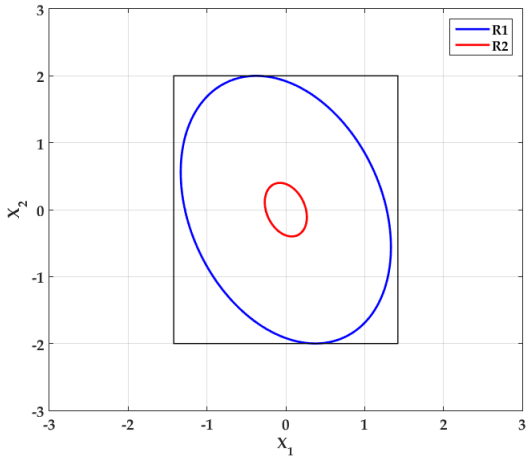


Fig. 6. Estimation of the DA for system Eq. (54) using quadratic LF (Blue ellipsoid using SBOA technique-Red ellipsoid using analytical technique).

The largest DA is represented by the blue ellipsoid in Fig. 6. Fig. 7 presents the evolution of the state space and the input control.

## VI. Discussion

This section seeks to compare the advantages of the current work's strategy with those of works presented in study [12] and study [2] as part of a bench-marking study. Table I summarizes the different results achieved for four dynamic nonlinear systems taking into account input saturation. The implementation of the SBOA method incorporates both quadratic Lyapunov functions. In this study, obtaining the maximum volume of the region of attraction serves as the primary criterion for evaluation. As far as the domain of attraction values are concerned, the results obtained are clearly superior. DA features are shown in table I for four nonlinear dynamic systems with quadratic Lyapunov functions. Systems of E1, E2 and E3 are second-order systems. However, E4 is a nonlinear third order system.

TABLE I. Summary of the Bench-Marking Comparative Study

| Example | System dynamic | Lyapunov Function | Estimation of DA | | Estimation of DA with SBOA | |
|---|---|---|---|---|---|---|
| | | | Polytope | Volume | Volume | Polytope |
| E1[12] | $\begin{cases} \dot{x}_1 = -2x_1 + x_1x_2 \\ \dot{x}_2 = x_1 + x_2 + x_1x_2 + sat(u) \end{cases}$ | Quadratic | $\begin{vmatrix} x_1 \\ x_2 \end{vmatrix} \vee \begin{vmatrix} 0.7, \\ 0.7 \end{vmatrix}$ | $v = 0.2421$ | $\begin{vmatrix} x_1 \\ x_2 \end{vmatrix} \vee \begin{vmatrix} 1.1889, \\ 0.80046 \end{vmatrix}$ | $v = 0.3251$ |
| E2[12] | $\begin{cases} \dot{x}_1 = \frac{1+x_1^2}{2}x_2 \\ \dot{x}_2 = \frac{2}{1+x_1^2}x_1 - x_2 - \frac{1-x_1^2}{1+x_1^2}sat(u) \end{cases}$ | Quadratic | $\begin{vmatrix} x_1 \\ x_2 \end{vmatrix} \vee \begin{vmatrix} 0.4, \\ 0.6 \end{vmatrix}$ | $v = 0.1024$ | $\begin{vmatrix} x_1 \\ x_2 \end{vmatrix} \vee \begin{vmatrix} 0.44745, \\ 0.94678 \end{vmatrix}$ | $v = 0.1116$ |
| E3 [52] | $\begin{cases} \dot{x} = \begin{bmatrix} 01 \\ -\frac{c_3}{M} - \frac{c_1+c_2x_1^2}{M} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1+c_4x_2^2}{M} \end{bmatrix} u, \\ y = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \end{cases}$ | Quadratic | $\begin{vmatrix} x_1 \\ x_2 \end{vmatrix} \vee \begin{vmatrix} 0.45, \\ 0.32 \end{vmatrix}$ | $v = 0.0679$ | $\begin{vmatrix} x_1 \\ x_2 \end{vmatrix} \vee \begin{vmatrix} 01.5, \\ 1.4018 \end{vmatrix}$ | $v = 1.0489$ |
| E4[28] | $\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \varepsilon_1 x_2 + \varepsilon_2 \tau_1 + \eta_1 \\ \dot{x}_3 = \cos x_1 x_2 \\ 0 = \tau_1 - \varepsilon_4 x_3 - \varepsilon_5 \cos x_1 \\ 0 = x_3^2 + \cos x_1^2 - 1 \end{cases}, x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ | Quadratic | $\begin{vmatrix} x_1 \\ x_2 \\ x_3 \end{vmatrix} \vee \begin{vmatrix} 1.1 \\ 1.1 \\ 8 \end{vmatrix}$ | $v = 0.0769$ | $\begin{vmatrix} x_1 \\ x_2 \\ x_3 \end{vmatrix} \vee \begin{vmatrix} 1.4984 \\ 1.5 \\ 2 \end{vmatrix}$ | $v = 0.2033$ |

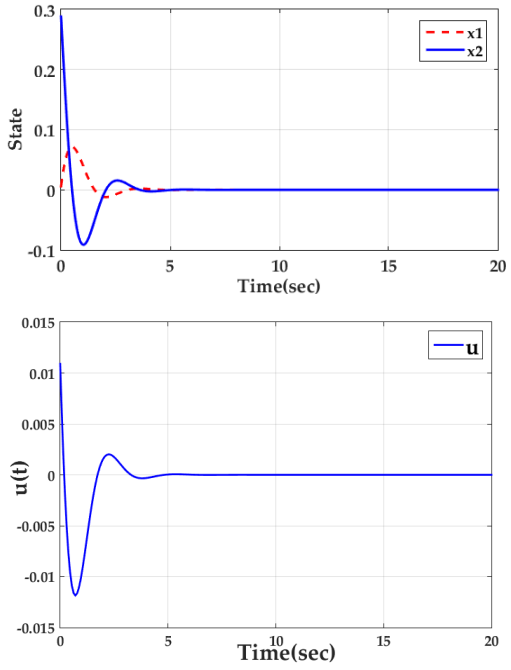


Fig. 7. Simulation results of example 2: states and input control.

The example 5.1 illustrates the advantage of a polynomial Lyapunov function over a quadratic Lyapunov function. Please be aware that the domain of volume serves as the primary evaluation factor. For each example, going through three stages using the SBOA approach, and comparing the results obtained by the technique presented in study [2].

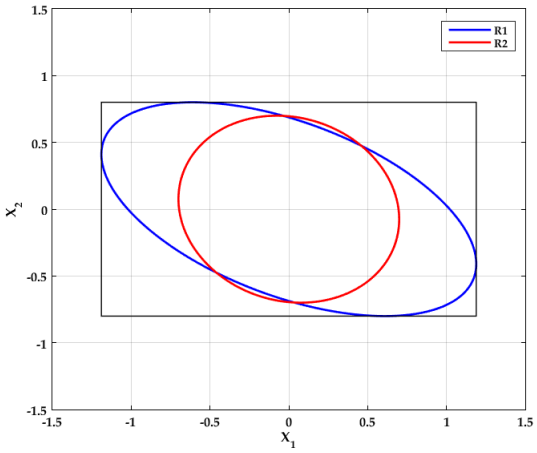


Fig. 8. DA that is approximation based on the SBOA approach for the origin in case E1 that is listed in Table I.

Fig. 8, 9, 10 and 11 illustrates the approximate domain of attraction for example E1-E4 described in Table I. The blue ellipsoid illustrates the estimated DA as determined by the SBOA method, while the red ellipsoid illustrates the estimated DA as determined by the approach described in study [2]. As a result, Fig. 12, 13, 14 and 15 depict the dynamic of state variables and their control inputs for each of the examples in Table I. A stable equilibrium point can be established asymptotically by the state variables. In this regard,

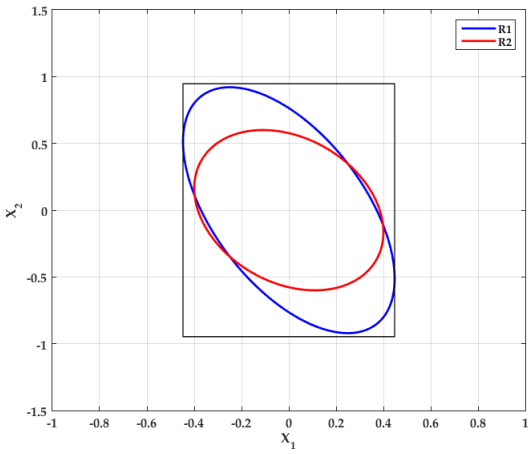


Fig. 9. DA that is approximation based on the SBOA approach for the origin in case E2 that is listed in Table I.

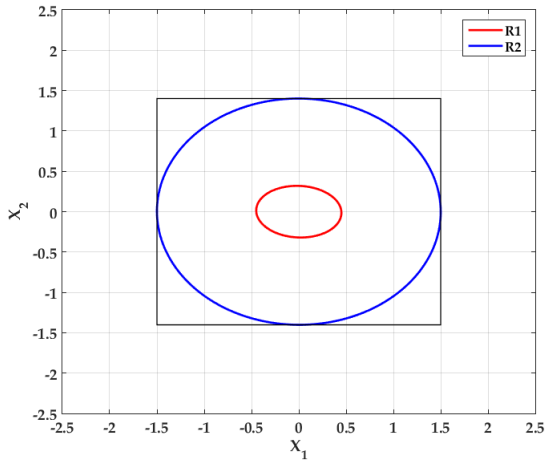


Fig. 10. DA that is approximation based on the SBOA approach for the origin in case E3 that is listed in Table I.

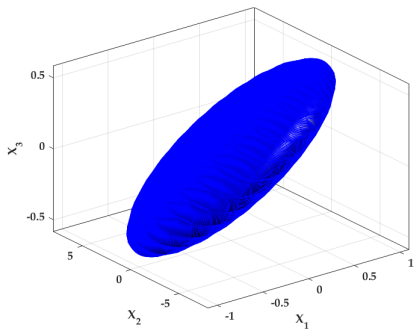


Fig. 11. DA that is approximation based on the SBOA approach for the origin in case E4 that is listed in Table I.

the strategy developed offers a complete solution that begins by guaranteeing the local stability of the system, then estimates the states admissible, and finally provides the maximal domain volume possible.

Furthermore, Table I clearly illustrates that, for the four examples studied, the SBOA technique yields significantly better estimates of the basin of attraction than the approach presented in study [2].

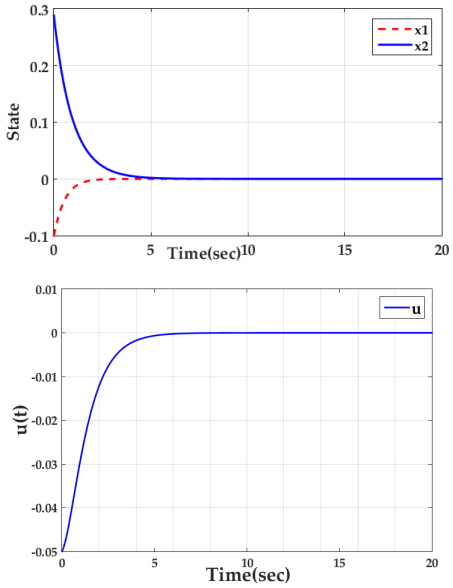


Fig. 12. Simulation results of example E1: states and input control.

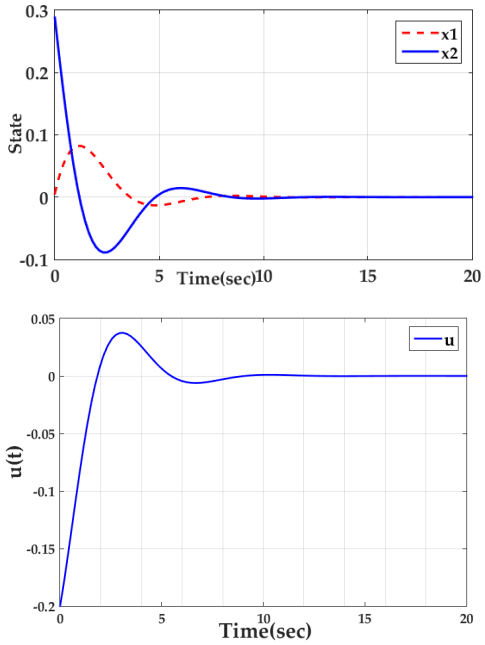


Fig. 13. Simulation E2; states and input control.

## VII. Conclusion

This paper discusses the concept of combining analytical and meta-heuristic approaches. This approach improve the performance of practical engineering systems using hybrid optimization techniques. Under the constraint of actuator saturation, the proposed method ensures high stability and efficiency. Among the fields of robotics and control, this is a well-known and sensitive issue. As a result, it is established that the developed technique maintains this feature and

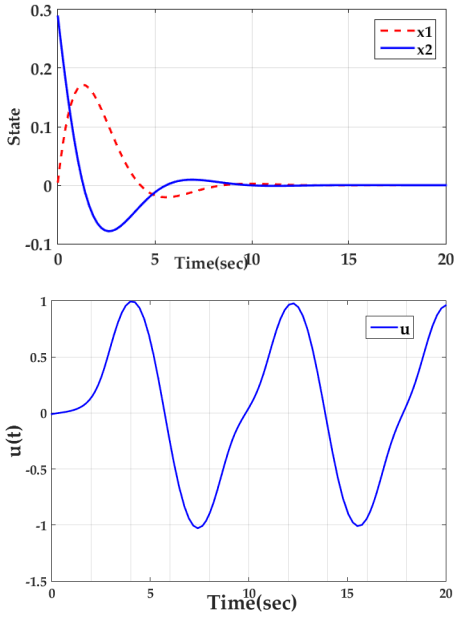


Fig. 14. Simulation results of E3; states and input control.

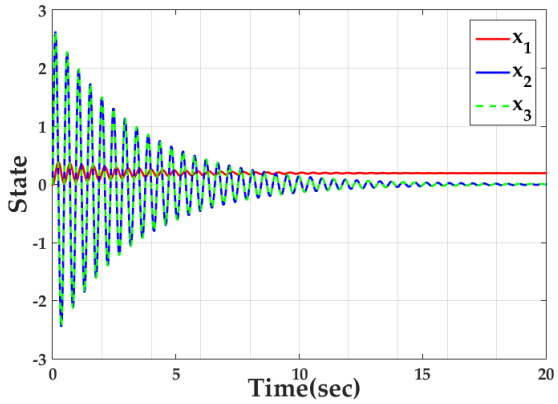


Fig. 15. Simulation results of E4; states.

ensures the reliability of controlled systems. Particularly, the method has been proven effective in controlling robot actuators. The study focuses on the maximization of the attraction region. Furthermore, the attraction region that is studied is deducible by the defined state space polytopic regions. The main idea is to combine the generalized sector condition, with the Finsler lemma and linear annihilator in order to reduce the conservativeness. The designed outline presented in this research relied on the central idea of computing best vertices of the polytypic and determining the associated optimal Lyapunov function to find the largest attraction region. To obtain the largest domain of attraction we implemented a meta-heuristic approach, with encoding the variable of the vertices of the polytope of admissible state to be determined as particle position was presented. The meta-heuristic technique introduced in this study is powerful in problem solving, and a very efficient global search algorithm. As well as the result, the numerical example shows that using meta-heuristic leads to the biggest DA. A novel perspective on the enlarging of the DA could be performed by implementing meta optimization method for tuning the controller gains of nonlinear system with input saturation and model parameter uncertainties.

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# Optimizing Data Transmission and Energy Efficiency in Wireless Networks: A Comparative Study of GA, PSO, and Hybrid Approaches

Suhare Solaiman
Department of Computer Science-College of Computers and Information Technology, Taif University
P.O. Box 11099, Taif 21944, Saudi Arabia

***Abstract*—As wireless communication technology evolves, efficient resource allocation in Orthogonal Frequency Division Multiple Access (OFDMA) networks is becoming more important. This study looks at three resource allocation algorithms: Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and a hybrid approach that combines both. The hybrid algorithm takes advantage of the strengths of both methods to improve data transmission and energy efficiency. Using simulations in MATLAB, the study assesses algorithms based on key metrics such as data rate, energy consumption, and computational complexity. The findings show that the hybrid approach generally performs better than both GA and PSO, especially in maximizing data rates. This research offers useful information for network operators looking to implement effective resource management strategies in practical wireless communication settings.**

***Keywords*—Resource allocation; optimization; genetic algorithms; particle swarm optimization; hybrid algorithm**

## I. Introduction

As wireless communication technology rapidly evolves, the importance of efficient resource allocation has increased. Orthogonal Frequency Division Multiple Access (OFDMA) networks are the foundation of modern communication, enabling everything from our smartphones to high-speed Internet connections. OFDMA divides the available bandwidth into multiple distinct subcarriers, allocating a unique set to each user. This separation allows users to communicate simultaneously without interference, ensuring a seamless and efficient experience [1] [2].

OFDMA is commonly used in various wireless communication standards, including WiMAX, LTE, and 5G networks. It effectively manages bandwidth, allowing multiple users to connect at the same time while keeping latency low and throughput high. By dynamically allocating subcarriers based on user demand and channel conditions, OFDMA improves overall network performance. This makes it a practical choice for modern networks, where reliable connections for activities, such as video streaming and online gaming are increasingly important [3].

In a world where staying connected is essential, the task of effectively distributing limited resources, such as bandwidth and power, has become more complicated than ever. Energy efficiency plays an important role, helping to lower operational costs for network providers, extend battery life for mobile devices, and reduce the environmental impact of increased technology use. Optimizing resource allocation is increasingly seen as both a practical necessity and a responsible choice. Implementing energy-efficient practices can help reduce carbon footprints and support efforts to address climate change.

To address these challenges, a variety of algorithms are adopted, each offering unique strengths and tailored solutions for resource allocation. For instance, the Water-Filling Algorithm is recognized as a fundamental method for distributing power according to the varying channel conditions of different users. This algorithm efficiently allocates power to users with better channel quality, thereby maximizing overall system performance [4] [5]. In addition, the Bisection Algorithm plays a crucial role by systematically narrowing the search for optimal solutions, ensuring effective and efficient resource utilization. Maintaining high quality of service is especially important in crowded networks as the number of connected devices and bandwidth demands increase [6] [7].

Adaptive resource allocation challenges can also be addressed using heuristics such as Genetic Algorithm (GA) [8] and Particle Swarm Optimization (PSO) [9]. GA draws inspiration from natural processes, beginning with a set of potential solutions that are refined over time through selection, crossover, and mutation. As these solutions evolve across multiple generations, they continuously improve, making GA particularly effective for complex problems that traditional methods may struggle to solve [10] [11]. On the other hand, PSO mimics the collective behavior of birds and fish. In this approach, each *particle* represents a potential solution that navigates the solution space based on its own experiences and those of its neighbors. The position of a particle is adjusted according to two factors: the best solution it has discovered and the locations of its neighbors. This collaborative effort enables PSO to explore the solution space effectively, often leading to optimal solutions in complex scenarios [12] [13]. The hybrid approach combines the evolutionary characteristics of GA with the collaborative search capabilities of PSO, resulting in a more robust and efficient method for optimizing data transmission and energy efficiency in OFDMA networks [14] [15].

In this study, a comprehensive comparison of three resource allocation algorithms is presented: GA, PSO, and a hybrid method that effectively combines the strengths of both GA and PSO. The evaluation will focus on key performance metrics such as data rate, energy consumption, and time complexity. By analyzing these algorithms across a range of scenarios, the study aims to identify the best algorithm in terms of data rates and energy consumption. The findings seek to bridge the gap

between theoretical models and practical applications, offering information that can enhance the operational efficiency of wireless networks. As the industry encounters increasingly complex and demanding environments, understanding how to optimize resource allocation will be essential for ensuring sustainable, high-quality service delivery. This research will contribute to informed decision making and strategic planning in resource management, ultimately supporting the evolving needs of modern communication systems.

### A. Contributions

This work offers several key contributions to the field of wireless communication:

- A comparative evaluation of three existing algorithms, GA, PSO, and a hybrid algorithm that combines GA and PSO, is presented to optimize data transmission and energy efficiency in wireless networks, highlighting their respective advantages and limitations.
- The preliminary results indicate that the proposed hybrid protocol outperforms the individual algorithms in key metrics, such as data rate and energy consumption, suggesting a more efficient use of resources.
- The findings provide practical guidelines for network operators seeking to implement more effective resource management strategies in real-world wireless communication scenarios.

## II. System Model and Problem Formulation

### A. System Model

In a single cell, there exists a collection of User Equipment (UE) devices that are tasked with transmitting data. Each device operates under specific power constraints, limiting the amount of transmit power it can utilize. In addition, these devices are allocated a portion of the available bandwidth, which restricts their data transmission capacity.

At the core of this network is a base station responsible for receiving data from all UE devices. This base station not only facilitates communication between the devices but also operates under its own set of power and bandwidth constraints, ensuring efficient data handling and network performance. To enhance this performance, OFDMA is utilized in this network. OFDMA allows multiple users to share the same frequency band by dividing it into numerous orthogonal subcarriers, enabling simultaneous transmission without interference. This approach optimizes bandwidth usage and improves overall system capacity, making it particularly effective in environments with varying channel conditions.

Each UE device has a transmit power used for communication, which is determined by regulatory limits and device capabilities. A finite total bandwidth $B_{\text{total}}$ is shared among all devices, necessitating effective scheduling and allocation methods to maximize throughput. OFDMA plays a crucial role in this allocation process, dynamically assigning subcarriers based on user demand and channel quality. Each device can transmit data for a certain time period, contributing to the overall energy consumption. This energy consumption is a critical factor, as it impacts the battery life of the devices and the overall sustainability of the network. Understanding the interplay of these constraints is essential for optimizing performance and ensuring reliable service delivery in wireless communication systems.

*1) Data transmission model:* The data rate for each device can be modeled using the Shannon capacity formula:

$$R_k = B_k \cdot \log_2 \left(1 + \frac{P_k}{N_0 \cdot B_k}\right), \tag{1}$$

where $R_k$ is the data rate of device $D_k$, $B_k$ is the bandwidth allocated to device $D_k$, $P_k$ is the power allocated to device $D_k$, and $N_0$ represents the spectral density of the noise power.

*2) Energy consumption:* The energy consumed by each device during transmission can be calculated as:

$$E_k = P_k \cdot T_k, \tag{2}$$

where $E_k$ is the energy consumed by device $D_k$ and $T_k$ is the transmission time for device $D_k$.

### B. Problem Formulation

The primary objective of the proposed resource allocation model is to maximize the total data rate across all devices while minimizing the overall energy consumption. This can be formulated as a multi-objective optimization problem:

$$\text{Maximize } \sum_{k=1}^{N} R_k - \lambda \sum_{k=1}^{N} E_k, \tag{3}$$

Subject to:

$$\text{C1: } \sum_{k=1}^{N} P_k \leq P_{\text{total}},$$
$$\text{C2: } \sum_{k=1}^{N} B_k \leq B_{\text{total}},$$
$$\text{C3: } \sum_{k=1}^{N} T_k \leq T_{\text{total}},$$

where where $N$ represents the total number of devices in the network. $R_k$ represents the data rate for device $D_k$; $P_k$ denotes the transmission power for device $D_k$; $T_k$ is the transmission time allocated for device $D_k$; $B_k$ is the bandwidth allocated to device $D_k$; and $h_k$ indicates the gain in the channel for device $D_k$. In constraint C1, the total power allocated to all devices should not exceed the maximum available power. In constraint C2, the total bandwidth allocated to all devices should not exceed the available bandwidth. In constraint C3, the total transmission time allocated to all devices must not exceed the maximum allowed transmission time.

The optimization problem here is mixed integer nonlinear programming (MINLP). Having integer and continuous decision variables leads to this classification. Mixing integers

means that some variables, such as the number of UE devices $N$, can have integer values, while others, such as power $P_k$, bandwidth $B_k$, and transmission time $T_k$, can have continuous values. Additionally, the objective function may include nonlinear relationships, such as maximizing total revenue minus a penalty for energy consumption. As a result, if any part of the objective function or constraints shows nonlinearity, the problem is classified as nonlinear. Due to this complexity, specialized algorithms are necessary for finding effective solutions.

## III. Optimization Techniques

To effectively solve the optimization problem defined in Eq. (3), population-based algorithms can be employed, including GA, PSO, and hybrid algorithm that combine the strengths of both GA and PSO.

### A. Resource Allocation Using GA

GAs utilize principles of evolution to optimize complex problems. They represent candidate solutions as chromosomes, employing a population-based approach where multiple solutions are evaluated concurrently. Each candidate solution is assessed based on an objective function, as defined in Eq. (3).

The selection process in GA strategically prioritizes fitter individuals, allowing them to pass advantageous traits to the next generation through mechanisms such as crossover (where parts of two parent solutions are combined) and mutation (where random alterations are made to a solution). This evolutionary strategy not only improves the quality of solutions, but also fosters genetic diversity within the population, which is essential to avoid local optima. To effectively manage constraints (C1, C2, and C3), GA often implements penalty functions. These penalties reduce the fitness scores of solutions that violate established constraints, thereby discouraging infeasible solutions. This mechanism promotes the exploration of viable solutions while ensuring a diverse search space. Such diversity is crucial for navigating complex non-linear optimization problems, enabling GA to discover high-quality solutions that satisfy all constraints.

A comprehensive overview of the processes involved in GA, including specific steps and methodologies, is shown in Table I.

TABLE I. Optimized Resource Allocation Using GA

**Input:**

- Population size $P$: Number of individuals in each generation.
- Number of generations $G$: Maximum iterations for the GA.
- Crossover rate $C_{\text{rate}}$: Probability of crossover between parents.
- Mutation rate $M_{\text{rate}}$: Probability of mutation for individuals.

**Output:**

- The best solution representing the optimal resource allocation with its fitness value.

1. **Initialize population:**
Each individual is represented by a random vector:

$$\text{individual}_i = \begin{pmatrix} P_1 & P_2 & \cdots & P_N \\ B_1 & B_2 & \cdots & B_N \\ T_1 & T_2 & \cdots & T_N \end{pmatrix} \tag{4}$$

2. **Evaluate Fitness:**
The fitness of each individual is evaluated based on the objective function:

$$\text{fitness}(\text{individual}_i) = \sum_{k=1}^{N} R_k - \lambda \sum_{k=1}^{N} E_k \tag{5}$$

Ensure that the individual satisfies the constraints $C_1, C_2$, and $C_3$. If constraints are violated, apply a penalty to the fitness score:

$$\text{fitness}(\text{individual}_j) = \begin{cases} \text{fitness}(\text{individual}_j) - P & \text{if constraints violated} \\ \text{fitness}(\text{individual}_j) & \text{otherwise} \end{cases} \tag{6}$$

3. **Selection:**

- Select parents based on fitness.
- Choose a predetermined number of parents to form a mating pool.

4. **Crossover:**

- For each pair of parents in the mating pool, generate $r$, which represents a random value generated uniformly within a specific range between $[0, 1]$.
- If $r < C_{\text{rate}}$, perform crossover to create offspring:

$$O = \begin{pmatrix} P_1[1:q] \\ P_2[q+1:N] \end{pmatrix} \tag{7}$$

where $q$ is a randomly chosen crossover point.

5. **Mutation:**

- Apply mutation to offspring based on the mutation rate:

$$O[j] = \begin{cases} O[j] + \Delta & \text{if } r < M_{\text{rate}} \\ O[j] & \text{otherwise} \end{cases} \tag{8}$$

where $\Delta$ is a random value drawn from a specified distribution. $j$-th offspring in the population array $O$.

6. **Evaluate offspring fitness:**

- For each offspring, calculate its fitness based on the resource allocation efficiency using equation (5).

7. **Replacement:**

- Form a new population by selecting the best individuals from both the current population and the new offspring.

8. **Termination:**

- If the maximum number of generations $G$ is reached or if a satisfactory solution (fitness) is found, stop the algorithm. Otherwise, return to step 3.

### B. Resource Allocation Using PSO

Social behaviors are replicated in PSOs by mimicking natural phenomena, such as flocks of birds or schools of fish. In this algorithm, particles represent potential solutions that dynamically adjust their positions in the search space based on both their individual experiences and the collective knowledge of the swarm. Each particle evaluates the objective function to determine its fitness, which guides its movement towards areas of higher quality solutions. The motion of a particle is influenced by two main factors: its previous best position and the best position found by any particle in the swarm. This dual influence allows PSOs to effectively balance exploration (searching new areas of the solution space) and exploitation (known good solutions). Additionally, when particle positions violate established constraints, PSOs typically employ strategies to either adjust the particles back into feasible regions or apply penalties that reduce their fitness scores. This penalty mechanism discourages the swarm from exploring infeasible solutions, thereby maintaining a focus on viable options. PSOs are particularly effective for continuous optimization problems, where the solution space is defined by real valued variables. The algorithm's inherent ability to adaptively explore while converging towards an optimal solution makes it suitable for a wide range of applications, including engineering design, machine learning parameter tuning, and resource allocation. Moreover, the simplicity of PSO, combined with its flexibility, allows it to be easily hybridized with other optimization techniques, further enhancing its performance in complex problem

TABLE II. OPTIMIZED RESOURCE ALLOCATION USING PSO

**Input:**

- Population size $P$: Number of particles in the swarm, determining the diversity of solutions.
- Maximum iterations $G$: The upper limit on the number of iterations for the PSO algorithm, defining its computational duration.
- Cognitive coefficient $c_1$: Weighting factor that influences how much each particle is attracted to its own best-known position.
- Social coefficient $c_2$: Weighting factor that influences how much each particle is attracted to the swarm's best-known position.

**Output:**

- The best solution found by the swarm along with its corresponding fitness value, indicating the effectiveness of the resource allocation.

1. **Initialize Swarm:**
Each particle $i$ is represented with a random position and velocity:

- The position vector for particle $i$ is defined as:

$$\mathbf{X}_i = \begin{pmatrix} P_1 & P_2 & \cdots & P_N \\ B_1 & B_2 & \cdots & B_N \\ T_1 & T_2 & \cdots & T_N \end{pmatrix} \tag{9}$$

  where $N$ is the number of devices or resources.
- The velocity vector for particle $i$ is defined as:

$$\mathbf{V}_i = \begin{pmatrix} v_{P1} & v_{P2} & \cdots & v_{PN} \\ v_{B1} & v_{B2} & \cdots & v_{BN} \\ v_{T1} & v_{T2} & \cdots & v_{TN} \end{pmatrix} \tag{10}$$

- Initialize each particle's best position $pbest_i$ to its initial position.

2. **Evaluate Fitness:**

- Calculate the fitness for each particle using the fitness function:

$$\text{fitness}(x_i) = \sum_{k=1}^{N} R_k - \lambda \sum_{k=1}^{N} E_k \tag{11}$$

  where $R_k$ represents the reward from resource $k$ and $E_k$ denotes the energy consumption.
- Update the particle's best position $pbest_i$ if the current position yields a better fitness value.
- Ensure that the constraints $C_1$, $C_2$, and $C_3$ are satisfied for each particle's position.

3. **Update global best:**

- Update the swarm's best position $gbest$ based on the best positions found by all particles.

4. **Update velocities and positions:**

- Update the velocity for each particle $i$:

$$v_i = w \cdot v_i + c_1 \cdot r_1 \cdot (pbest_i - x_i) + c_2 \cdot r_2 \cdot (gbest - x_i) \tag{12}$$

- Update the position for each particle $i$:

$$x_i = x_i + v_i \tag{13}$$

- Re-evaluate $C_1$, $C_2$, and $C_3$ after updating positions to ensure validity.

5. **Termination:**

- The algorithm stops if the maximum number of iterations $G$ is reached or if a satisfactory solution based on fitness is found.
- If neither condition is met, return to step 2 for further iterations.

domains.

A complete overview of the processes involved in PSO, including specific steps and methodologies, is illustrated in Table II.

### C. Resource Allocation using Hybrid Algorithm

In hybrid algorithm, GA and PSO are integrated to improve overall optimization performance. This combination leverages the strengths of both techniques: initial solutions are generated using genetic principles, which emphasize diversity and broad exploration, while subsequent refinements are achieved through swarm intelligence, which focuses on effective local search. By merging these two algorithms, hybrid algorithm can take advantage of the advantages of genetic operations, such as cross-linking and mutation, to explore a wide solution space. This broad exploration is critical for identifying promising regions in complex landscapes. Once potential solutions are identified, the dynamics of the swarm come into play, allowing for precise fine-tuning of these solutions based on the collective knowledge of the swarm. This dual approach improves the convergence speed and the quality of the solution. Moreover, the hybrid algorithm employs penalty mechanisms to handle constraint violations, similar to traditional GA and PSO. By discouraging infeasible solutions, this algorithm maintains a focus on viable options, ensuring that the search remains within the bounds of acceptable solutions. This capability is especially advantageous in complex optimization scenarios where constraints are stringent and multifaceted.

The hybrid approaches are particularly effective for tackling challenging optimization problems, as they can successfully navigate both local and global search spaces. The combination of exploratory genetic principles with the exploitative strengths of swarm intelligence enables this algorithm to escape local optima while still converging toward high-quality global solutions. This versatility makes the hybrid algorithm suitable for a wide range of applications, including engineering design, logistics, financial modeling, and machine learning, where the complexity of the problem demands a robust and adaptive optimization strategy.

A comprehensive overview of the processes involved in the hybrid approach, including specific steps and methodologies, is shown in Table III.

## IV. SIMULATION AND RESULTS

The network for the study was simulated using MATLAB, a widely used tool for numerical analysis and data visualization. GA, PSO, and the hybrid algorithm are implemented to assess their effectiveness in resource allocation. The simulation allowed for easy adjustment of parameters and visualization of results in real time, providing insights into network performance under different conditions.

The time complexities associated with solving the resource allocation problem in OFDMA networks vary significantly among the algorithms employed. The GA exhibits a time complexity of $O(P \cdot G \cdot N)$, where $P$ denotes the size of the population, $G$ represents the number of generations, and $N$ corresponds to the number of User Equipment (UE) devices. This complexity arises from the need to evaluate and evolve a population of candidate solutions over multiple generations, each requiring assessment of the fitness of $N$ devices. In parallel, the PSO algorithm demonstrates a time complexity of $O(S \cdot G \cdot N)$, where $S$ indicates the swarm size. As with GA and PSO, the iterative process of updating particle (potential solution) positions based on their own and their peers' experience drives the complexity, requiring evaluations across all $N$ devices in each generation.

In contrast, the hybrid algorithm, which integrates elements of both GA and PSO, incurs a time complexity of $O((P + S) \cdot G \cdot N)$. This reflects the necessity to evaluate the fitness of both populations on each iteration: the particles generated by the GA and the particles from the PSO. As a

result, this algorithm may provide a more thorough exploration of the solution space, but at the cost of increased computational complexity. However, all three algorithms exhibit a dependency on the sizes of their respective populations or swarms, the number of generations or iterations, and the number of devices involved. This relationship underscores the computational effort required for larger networks, highlighting a critical consideration for practitioners in the field. As the number of UE devices increases, the time complexity can lead to significant delays in real-time applications. Therefore, optimizing these algorithms or developing hybrid algorithms that can reduce time complexity while maintaining solution quality is essential for scalable and efficient resource allocation in OFDMA networks.

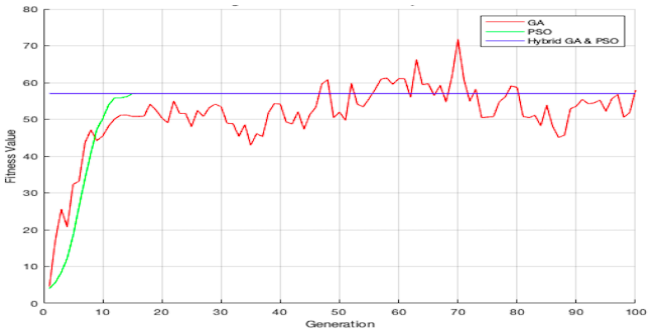


Fig. 1. Comparison of fitness values across generations for GA, PSO, and the hybrid algorithm.

Fig. 1 presents an analysis of the performance of various algorithms in terms of their fitness values. The results clearly indicate that the hybrid approach, which combines GA and PSO, is the most effective in consistently achieving higher fitness values compared to either algorithm used in isolation. The observed performance trends highlight that while PSO tends to provide stable solutions with less variability, the hybrid model effectively leverages the strengths of both algorithms. By utilizing GA's exploratory capabilities to navigate the solution space and PSO's ability to refine and converge on optimal solutions, the hybrid approach demonstrates superior performance across various scenarios. Furthermore, the adaptability of the hybrid algorithm enables it to function effectively in a variety of settings and complex problems, indicating its possible use in real-world situations where environmental changes could occur.

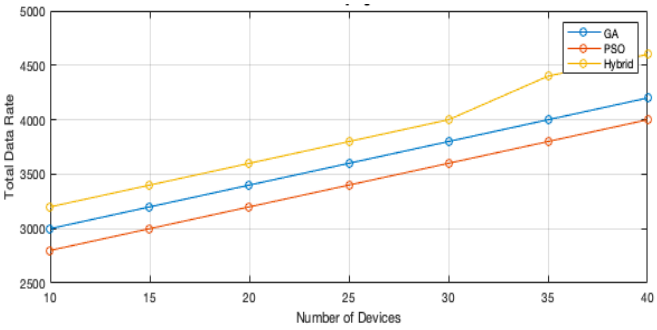


Fig. 2. The total data rate versus the number of devices for GA, PSO, and the hybrid algorithm.

Fig. 2 illustrates a comprehensive analysis of the performance of three algorithms in relation to the total data rate as the number of devices increases. The data reveals a clear trend: all three algorithms demonstrate an improvement in total data rate with the addition of more devices. This improvement highlights the algorithms' ability to effectively utilize available resources as network demand grows. Among the algorithms tested, the hybrid algorithm emerges as the most effective solution, consistently achieving the highest data rates across varying device counts. This superior performance may be attributed to its unique approach, which likely combines the strengths of both traditional and modern techniques, allowing for more adaptable resource allocation and enhanced management of network traffic.

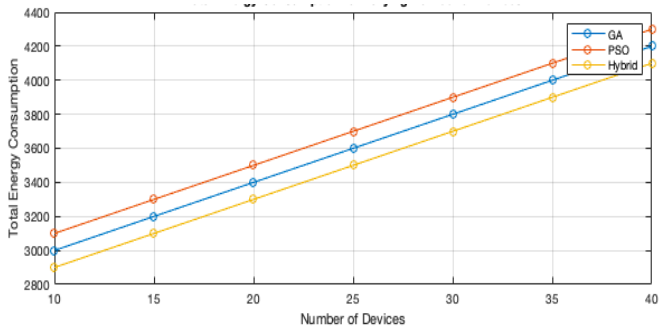


Fig. 3. The power consumption versus the number of devices for GA, PSO, and the hybrid algorithm.

The analysis in Fig. 3 indicates that as the number of devices increases, the energy consumption of all algorithms increases. In spite of its superior data rate performance, the hybrid approach uses the most energy, while GA and PSO exhibit the most efficient energy usage. This shows that trade-offs between energy efficiency and performance, especially in larger networks, need to be carefully considered. In order to better balance these factors, future research could concentrate on improving the hybrid approach. The strong performance of the hybrid algorithm indicates its potential for better resource management and performance optimization, especially in larger networks where device density can significantly affect data transmission efficiency. It could prove a fantastic option for deployment in environments with high user demand because of its capacity to maintain high data rates even as the number of devices increases.

Future work should delve deeper into the specific configurations that contribute to the hybrid algorithm's success. Identifying optimal parameter settings and operational strategies could further enhance its efficacy. Additionally, further investigations into the scalability of this algorithm are essential, as understanding its limits and capabilities in increasingly complex network environments will be crucial for real-world applications. This could involve exploring its performance under varying network conditions, different types of traffic loads, and integration with emerging technologies such as Internet of Things (IoT) and 5G networks.

## V. Conclusion

In conclusion, this study highlights the significance of efficient resource allocation in OFDMA networks as a means

TABLE III. OPTIMIZED RESOURCE ALLOCATION USING HYBRID ALGORITHM (GA-PSO)

**Input:**

- Population size $P$: Number of individuals/particles in the population.
- Maximum iterations $G$: Total number of iterations for the hybrid algorithm.
- Crossover rate $C_{\text{rate}}$: Probability of crossover between individuals.
- Mutation rate $M_{\text{rate}}$: Probability of mutation for individuals.
- Cognitive coefficient $c_1$: Weight for the individual particle's best position.
- Social coefficient $c_2$: Weight for the swarm's best position.

**Output:**

- The best solution found by the hybrid algorithm, along with its fitness value.

1. **Initialize population and swarm:**

- Each individual $j$ is represented by a random vector:

$$\text{individual}_j = \begin{pmatrix} P_1 & P_2 & \cdots & P_N \\ B_1 & B_2 & \cdots & B_N \\ T_1 & T_2 & \cdots & T_N \end{pmatrix} \tag{14}$$

- Swarm particles $i$ are represented by a random position and velocity vector:

$$\mathbf{X}_i = \begin{pmatrix} P_1 & P_2 & \cdots & P_N \\ B_1 & B_2 & \cdots & B_N \\ T_1 & T_2 & \cdots & T_N \end{pmatrix} \tag{15}$$

$$\mathbf{V}_i = \begin{pmatrix} v_{P1} & v_{P2} & \cdots & v_{PN} \\ v_{B1} & v_{B2} & \cdots & v_{BN} \end{pmatrix} \tag{16}$$

- Initialize each particle's best position $pbest_i$ to its initial position.

2. **Evaluate fitness:**

- For each particle $i$ and individual $j$, calculate fitness based on the objective function:

$$\text{Fitness}(\mathbf{x}_i) = \sum_{k=1}^{N} R_k - \lambda \sum_{k=1}^{N} E_k \tag{17}$$

where $R_k$ represents the reward and $E_k$ the energy consumption for task $k$.

- Ensure that the individual satisfies the constraints $C_1$, $C_2$, and $C_3$: If constraints are violated, apply a penalty to the fitness:

$$\text{fitness}(\text{individual}_j) = \begin{cases} \text{fitness}(\text{individual}_j) - P & \text{if constraints violated} \\ \text{fitness}(\text{individual}_j) & \text{otherwise} \end{cases} \tag{18}$$

3. **Update global best:**

- Determine the best position $gbest$ across all particles and individuals to guide future movements.

4. **Update individuals:**

- Select individuals based on fitness to form a mating pool.
- For selected individuals, perform crossover based on $C_{\text{rate}}$:

$$O[g] = \begin{pmatrix} P_1[1:q] \\ P_2[q+1:N] \end{pmatrix} \tag{19}$$

where $q$ is a randomly chosen crossover point.

- Apply mutation based on $M_{\text{rate}}$ to introduce variability:

$$O[g] = \begin{cases} O[g] + \Delta & \text{if } r < M_{\text{rate}} \\ O[g] & \text{otherwise} \end{cases} \tag{20}$$

where $\Delta$ is a specified distribution random value.

5. **Update velocities and positions:**

- Update velocity for each particle $i$:

$$v_i = w \cdot v_i + c_1 \cdot r_1 \cdot (pbest_i - x_i) + c_2 \cdot r_2 \cdot (gbest - x_i) \tag{21}$$

- Update position for each particle $i$:

$$x_i = x_i + v_i \tag{22}$$

6. **Replacement:**

- Form a new population by selecting the best individuals from both the current population and the new offspring $O[g]$.

7. **Termination:**

- If the maximum number of iterations $G$ is reached or if a satisfactory solution based on fitness is found, stop the algorithm. Otherwise, return to step 2.

to meet the growing demand for seamless connectivity and energy efficiency. By comparing GA, PSO, and the hybrid algorithm, the hybrid approach effectively balances the benefits of both methodologies, resulting in superior performance in optimizing data transmission and energy consumption. The findings emphasize the importance of adapting resource allocation strategies to the dynamic conditions of modern wireless environments. Future research could explore further enhancements to the hybrid algorithm and investigate its scalability across different network configurations.

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# Enhancing Precision Agriculture with YOLOv8: A Deep Learning Approach to Potato Disease Identification

Mohammed Aleinzi
Faculty of Computing and Information Technology, Information System Department
Northern Border University, Saudia Arabia

***Abstract*—Timely and precise identification of potato leaf diseases plays a critical role in improving crop productivity and reducing the impact of plant pathogens. Conventional detection techniques are often labor-intensive, dependent on expert analysis, and may not be practical for widespread agricultural use. This paper introduces an automated detection system based on YOLOv8, a cutting-edge deep learning framework specialized in object detection, to accurately recognize multiple potato leaf diseases. The proposed model is trained on a carefully prepared dataset that includes both healthy and infected leaves, utilizing robust feature learning to distinguish between different disease types. Our experimental evaluation reveals that the YOLOv8-based method achieves superior performance in terms of accuracy and processing speed when compared to traditional approaches. This work contributes to the ongoing transformation of agriculture through smart technologies by offering an AI-powered tool that facilitates real-time crop monitoring. Future research may focus on deploying this solution on edge devices, such as smartphones or drones, to enable scalable, on-field disease diagnostics. Ultimately, this study supports the vision of sustainable agriculture by integrating intelligent systems into everyday farming operations.**

***Keywords*—Potato disease detection; YOLOv8; Agriculture 4.0; deep learning**

## I. Introduction

Agriculture plays a pivotal role in global economic growth and food security, particularly in rural areas where a significant portion of the population depends on farming for their livelihood. According to reports, nearly 80% of rural inhabitants are engaged in agricultural activities [1]. However, food security remains a major challenge due to various factors, including plant diseases that threaten crop yields. Among staple crops, the potato is one of the most widely cultivated and economically significant vegetables. It ranks as the third most important crop after rice and wheat in several countries, contributing substantially to national food supplies and economic stability. Although potato cultivation plays a critical role in agricultural systems, it remains highly susceptible to numerous diseases, as extensively reported in previous research [2]. Without timely detection and effective management, these diseases can lead to significant reductions in both yield and quality.

Early detection of potato diseases is crucial to mitigating potential losses and ensuring sustainable agricultural practices. Traditional methods of disease identification often rely on expert observation and laboratory testing, which can be time-consuming, expensive, and inaccessible to small-scale farmers. As a result, researchers have increasingly turned to artificial intelligence (AI) and computer vision techniques to automate the process of plant disease detection. Convolutional neural networks (CNNs) and other deep learning and machine learning advancements have shown great promise in accurately diagnosing plant diseases [3].

A wide range of research efforts has been dedicated to leveraging machine learning techniques for the classification of plant diseases. Initial contributions in this area often focused on conventional algorithms, including Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN), which were employed to build predictive models capable of identifying various plant health conditions. Previous studies [4] have employed multiclass support vector machines (SVMs) on segmented potato leaf images, demonstrating significant effectiveness in accurately classifying various leaf diseases. Other researchers [5] have combined k-means clustering for image segmentation with machine learning classifiers, demonstrating a broad range of accuracy rates depending on the dataset and feature extraction techniques employed.

With the rise of deep learning, CNN-based models have become increasingly popular for plant disease detection. Several works [6] have applied well-known architectures, including VGG16, ResNet50, and MobileNet, to classify potato leaf diseases. Researchers have also experimented with transfer learning techniques to enhance classification performance. Previous studies in [7] utilizing the PlantVillage dataset, one of the most widely used open-source datasets for plant disease research, have reported high classification accuracies using deep learning models.

Recent advancements have also focused on hybrid models that integrate different techniques to improve classification performance. Researchers in study [8] have proposed using structured residual dense networks to reduce computational complexity while maintaining high accuracy. Others have explored feature selection techniques combined with deep learning to enhance model efficiency. Furthermore, lightweight models such as MobileNetV2 have been developed for real-time applications, achieving competitive results with minimal computational resources [9].

Despite these advancements, challenges remain in plant disease detection, particularly regarding dataset availability and model generalization. While many studies rely on PlantVillage or similar datasets, there is a growing need for diverse, real-world datasets that capture variations in environmental con-

ditions, lighting, and disease severity. Some researchers have attempted to address this limitation by collecting their own datasets, but these datasets are often not publicly available, limiting reproducibility and comparative analysis [10].

Building upon recent progress in deep learning and the emergence of Agriculture 4.0, this research introduces a detection strategy based on YOLOv8 for identifying diseases affecting potato leaves. As a cutting-edge object detection architecture, YOLOv8 is particularly well-suited for precision agriculture due to its ability to perform rapid and accurate inference in real time. Unlike traditional classification models, YOLOv8 can detect multiple disease regions within a single image, providing a more comprehensive assessment of plant health [11] [12] [13].

This study aims to enhance the accuracy and efficiency of potato disease detection by leveraging image segmentation techniques alongside deep learning. By training the model on a curated dataset of diseased and healthy potato leaves, this research seeks to improve disease classification performance compared to existing approaches. While this work primarily focuses on model development and evaluation, future research could explore the integration of this system into mobile or edge computing devices, aligning with the principles of Agriculture 4.0 to enable real-time, AI-driven disease diagnostics in the field. By advancing automated plant disease detection, this study contributes to the broader goal of precision agriculture, where AI-powered solutions enhance crop monitoring, reduce losses, and support sustainable farming practices.

The structure of the paper is organized as follows: Section II presents the related work. Section III details the proposed methodology, encompassing dataset collection, preprocessing strategies, and the fine-tuning process of the YOLOv8 model. Section IV reports the experimental results, accompanied by a thorough performance evaluation and analysis. In Section V, a comparative assessment is conducted against existing state-of-the-art detection approaches. Section VI highlights the detection outcomes achieved by the proposed model. Lastly, Section VII concludes the paper by summarizing the principal findings and outlining possible directions for future research. Section VIII introduces future work related to this study.

## II. Related Work

In recent years, artificial intelligence and computer vision have seen remarkable advancements, offering effective solutions for the complex task of plant disease identification. Initial approaches primarily relied on classical machine learning algorithms, such as Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN). For example, the study in [4] employed multiclass SVM models combined with segmentation techniques to classify potato leaf diseases with reasonable accuracy. Similarly, the study in [5] used graph cut segmentation prior to classification, highlighting the importance of preprocessing in improving model performance.

With the evolution of deep learning, CNNs became the dominant paradigm due to their ability to automatically extract hierarchical features from images. Architectures like VGG16, ResNet50, and MobileNet have been widely adopted in plant pathology applications [6]. Many studies have utilized the PlantVillage dataset, a benchmark resource for plant disease classification, achieving high accuracy using pretrained CNNs and transfer learning strategies [7]. These models demonstrated strong generalization in controlled conditions but often lacked robustness in real-world scenarios due to limited dataset diversity.

To overcome the limitations of standard CNNs, hybrid models have been proposed. These models combine the strengths of deep networks and optimization algorithms or incorporate handcrafted features to enhance disease recognition. For instance, the study in [8] introduced a structured residual dense network to reduce computational load while maintaining performance. Lightweight models like MobileNetV2 have also been explored for real-time mobile deployment, offering a balance between speed and accuracy [9].

Recent research has shifted towards object detection techniques, which provide spatial localization in addition to classification. The YOLO (You Only Look Once) family of models has gained prominence for its real-time capabilities. Studies have compared different YOLO versions (e.g., YOLOv5, YOLOv8) for plant disease detection tasks. For example, [25] conducted a comparative analysis of YOLOv5 and YOLOv8 in detecting corn leaf diseases, highlighting YOLOv8's superior detection accuracy and faster inference speed. Similarly, [24] evaluated YOLOv8 and YOLOv9 in hydroponic environments and confirmed YOLOv8's robustness in complex agricultural scenes.

Moreover, the introduction of specialized architectures such as SIS-YOLOv8 has further improved the adaptability of detection models to agricultural conditions. In [26], a deep learning-enhanced version of YOLOv8 was used for Solanaceae crop monitoring, integrating segmentation-based improvements to boost detection performance under various environmental constraints.

Despite these advancements, challenges persist in dataset generalization, annotation consistency, and deployment on low-power edge devices. Many studies still depend heavily on curated datasets like PlantVillage, which may not reflect real field variability. This highlights the need for research focusing on real-world datasets and robust models that can maintain performance across diverse conditions.

In response to these challenges, this work builds on the strengths of YOLOv8, leveraging its advanced architecture for accurate and efficient detection of multiple disease regions within potato leaves. By curating and annotating a diverse dataset and integrating fine-tuned segmentation techniques, our approach aims to bridge the gap between high-performance research models and practical agricultural applications.

## III. POTATNET: Fine-Tuned YOLOv8 for Potatoes Leaf Disease Detection

The YOLO series represents a deep learning framework tailored for object detection tasks. YOLOv8, an advancement over YOLOv5 by the same development team, retains the core architectural principles while incorporating notable optimizations and enhancements. This latest iteration surpasses YOLOv5 in algorithmic efficiency and versatility, enabling not only object detection and tracking but also additional functionalities as well as instance segmentation, image classification,

and keypoint detection. Expanding upon the foundation established by YOLOv5, YOLOv8 introduces key modifications that extend its applicability beyond conventional object recognition to more specialized tasks.

For this study, we employ a fine-tuned version of YOLOv8 optimized for detecting and classifying potato leaf diseases. The model is trained to accurately segment and classify various leaf infections, which is crucial for early disease diagnosis and precision agriculture. The architecture follows the five YOLOv8 model variants: n, s, m, l, and x, each progressively increasing in depth and width. Aligning with the ELAN design strategy [14], our fine-tuned YOLOv8 improves upon the YOLOv5 backbone by replacing the C3 module with the C2f structure, enhancing gradient flow and feature representation while maintaining computational efficiency.

A key enhancement in the fine-tuned YOLOv8 architecture is the integration of a decoupled head design, which enhances loss computation and optimizes feature extraction for segmentation-based tasks. The model utilizes the TaskAlignedAssigner technique [15] to refine loss function computation and incorporates the distribution focal loss function [16] to improve localization accuracy. To further enhance generalization, the fine-tuned YOLOv8 optimizes its data augmentation strategy by disabling Mosaic augmentation—originally introduced in YOLOX [17]—during the final training epochs, resulting in improved precision for leaf disease detection. Additionally, the YOLOv8 object detection framework includes segmentation-optimized variants, YOLOv8s-Seg and YOLOv8n-Seg. Inspired by the YOLACT network, these models achieve high segmentation mean average precision while enabling real-time instance segmentation. Fig. 1 illustrates the YOLACT network architecture [18].

The architecture of our fine-tuned YOLOv8 model consists of two fundamental components: the backbone and the head, where the latter is further divided into the neck and segmentation layers. Fig. 2 illustrates the modified network, optimized specifically for instance segmentation in potato leaf disease classification. The backbone integrates a 3×3 convolutional layer, the C2f module, and the Spatial Pyramid Pooling Fusion (SPPF) component. To enhance efficiency, we replace the standard 6×6 convolution in YOLOv5 with a 3×3 convolution. Additionally, the C2f module replaces the conventional C3 component to facilitate improved gradient propagation and feature extraction through optimized residual connections. The fine-tuned model also integrates two forms of the Cross-Stage Partial Network (CSP), applying residual connections in the backbone and direct connections in the head component [19]. The SPPF module, utilizing sequential 5×5 pooling kernels, remains aligned with YOLOv5 (version 6.1) for computational efficiency.

The head module comprises the neck and segmentation layers. The neck component integrates feature fusion networks such as the PANet [20] and FPN [21], ensuring effective multi-scale feature extraction. Unlike previous YOLO versions, including YOLOv5 and YOLOv6, our fine-tuned YOLOv8 eliminates the need for a 1×1 convolution before upsampling, opting instead for direct fusion of feature maps across different backbone stages.

To further enhance performance, we introduced key modifications to the neck module. Two 1x1 SimConv convolutions were used to enhance feature map aggregation and spatial information retention before every upsampling step. Additionally, 3×3 SimConv convolutions replace traditional convolutions in the neck, extending the receptive field and enhancing feature extraction capabilities. Moreover, we substituted the C2f module with the RepBlock module, which consists of stacked RepConv convolutions [22] designed for computational efficiency and optimized residual connections. This structural refinement ensures better gradient flow, improves parameter utilization, and enhances feature representation—key factors in achieving high-precision potato leaf disease detection.

By integrating these modifications, our fine-tuned YOLOv8 model achieves superior accuracy and efficiency in classifying and segmenting diseased potato leaves. The optimized architecture facilitates real-time detection, making it an effective tool for agricultural disease monitoring and precision farming applications.

## IV. Experiments and Results

### A. Evaluation Metrics

To evaluate the performance of the fine-tuned YOLOv8 model, both the training and validation datasets were employed. The assessment was carried out using standard object detection and segmentation metrics, with a particular focus on Average Precision (AP), which is calculated at various Intersection over Union (IoU) thresholds. These metrics provide a solid framework for measuring the accuracy and completeness of the model's predictions.

The IoU is a crucial metric that measures the degree of overlap between the predicted and ground truth regions. It is computed as the ratio of the area of overlap to the area of union between the two regions. An IoU of 1.0 represents a perfect match, while an IoU of 0 indicates no overlap. Based on the chosen IoU threshold, predictions are classified into different categories, including True Positive (TP), False Positive (FP), or False Negative (FN). Though not commonly used in segmentation tasks, a True Negative (TN) can also be considered, referring to accurately identified background regions.

To evaluate the model's capacity for object detection and localization, three important metrics were used: Precision, Recall, and the F1 Score. Precision is defined as the ratio of true positive predictions to the total number of predicted positives, reflecting the accuracy of the model's positive predictions. Recall is the proportion of true positives relative to the total number of actual positive instances, indicating the model's ability to correctly detect all relevant cases. The F1 Score, which combines both precision and recall, is calculated as the harmonic mean of these two metrics, offering a balanced evaluation when both precision and recall are equally important.

In addition to these metrics, for segmentation tasks, the performance of the model was also evaluated using mAP, particularly at an IoU threshold of 0.5. This value, referred to as mAP@0.5, summarizes the precision across all classes detected by the model, providing a comprehensive measure of its performance.

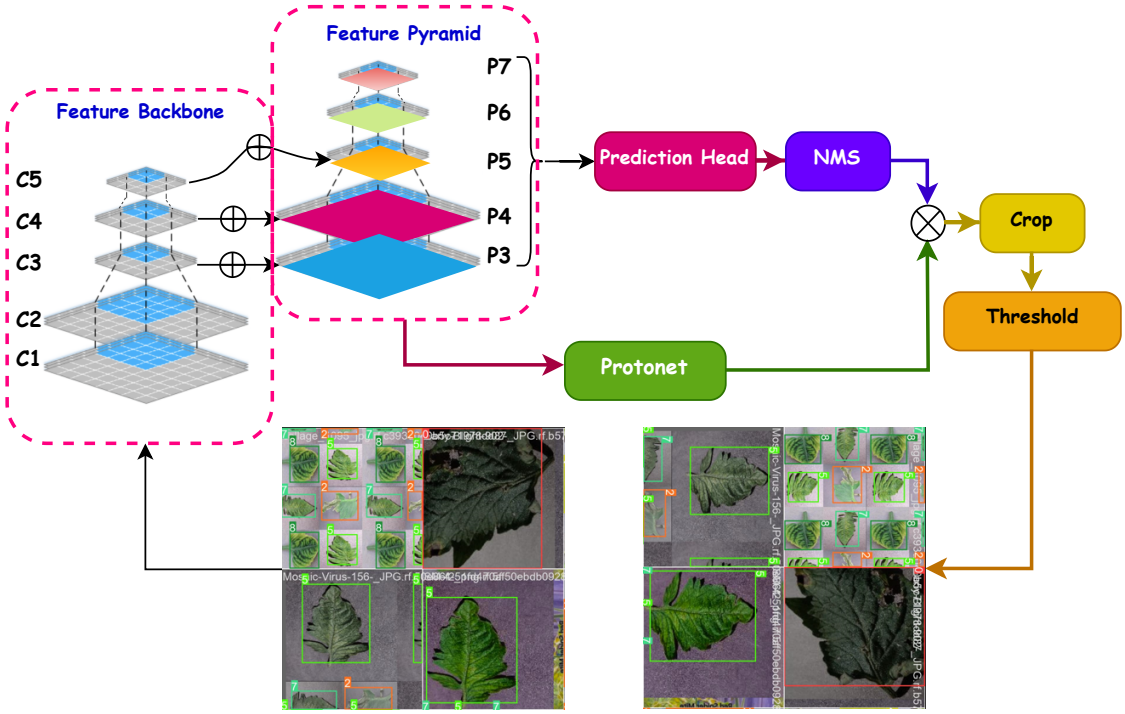



Fig. 1. YOLACT Architecture.

### B. Potatoes Leaf Disease Dataset

The used dataset in this study, generated via the Roboflow platform [23], was designed to support the training of deep learning models in detecting potato leaf diseases. It includes nine clearly defined classes like Early Blight, Healthy, Late Blight, Leaf Miner, Leaf Mold, Mosaic Virus, Septoria, Spider Mites, and Yellow Leaf Curl Virus. The data is split into training and validation subsets to ensure a robust learning process and reliable evaluation. Before training, all images underwent preprocessing, including automatic orientation correction to ensure a consistent viewpoint. A range of augmentation techniques was also applied to improve the model's generalization to different conditions. These augmentations included horizontal flipping, adjustments to brightness and contrast, Gaussian blurring, and random rotation. Such techniques introduce greater variability into the training data, enabling the model to better recognize disease symptoms across diverse scenarios. Thanks to its thoughtful structure and comprehensive preprocessing, this dataset represents a valuable asset for advancing research in automated plant disease detection and precision agriculture.

*1) Dataset distribution:* The analysis of the Potatoes dataset, as shown in Fig. 3, reveals a detailed distribution of instances across various disease categories, ensuring a balanced and representative coverage of the major plant conditions. The dataset includes a diverse range of leaf conditions, covering both healthy samples and various disease types such as Early Blight, Late Blight, and Septoria. It also encompasses instances of Leaf Mold, Mosaic Virus, and Yellow Leaf Curl Virus, along with damage caused by pests like Spider Mites and Leaf Miners.

Yellow Leaf Curl Virus emerges as the most common class, with around 5200 labeled instances, highlighting its significant presence in the dataset. On the other hand, Spider Mites is the least represented class, with approximately 2900 samples, indicating a lower frequency of occurrence. The remaining classes are distributed as follows: Early Blight with about 3000 instances, Healthy with 3500, Late Blight with 4200, Leaf Miner with 3200, Leaf Mold with 4000, Mosaic Virus with 3900, and Septoria with 3800 instances. Additionally, scatter plots provide insights into the distribution of bounding box annotations using normalized coordinates—specifically the center points (x, y) and dimensions (width, height). These visual representations underscore the variability in the dataset, which is essential for developing deep learning models capable of robust generalization across diverse visual symptoms of plant diseases.

*2) Dataset correlogram:* The correlogram depicted in Fig. 4 offers a comprehensive graphical analysis of the annotation features within the Potatoes dataset. It visualizes the relationships among key variables such as the normalized x and y positions, bounding box width, and height. The diagonal subplots represent the distribution of each individual feature, where noticeable peaks in the x and y axes indicate that object annotations are concentrated in particular regions of the images. The lower triangle of the correlogram, containing scatter plots, reveals inter-variable dependencies. Notably, a strong positive correlation is observed between bounding box width and height, suggesting that larger objects tend to maintain consistent aspect ratios. Additionally, the spatial

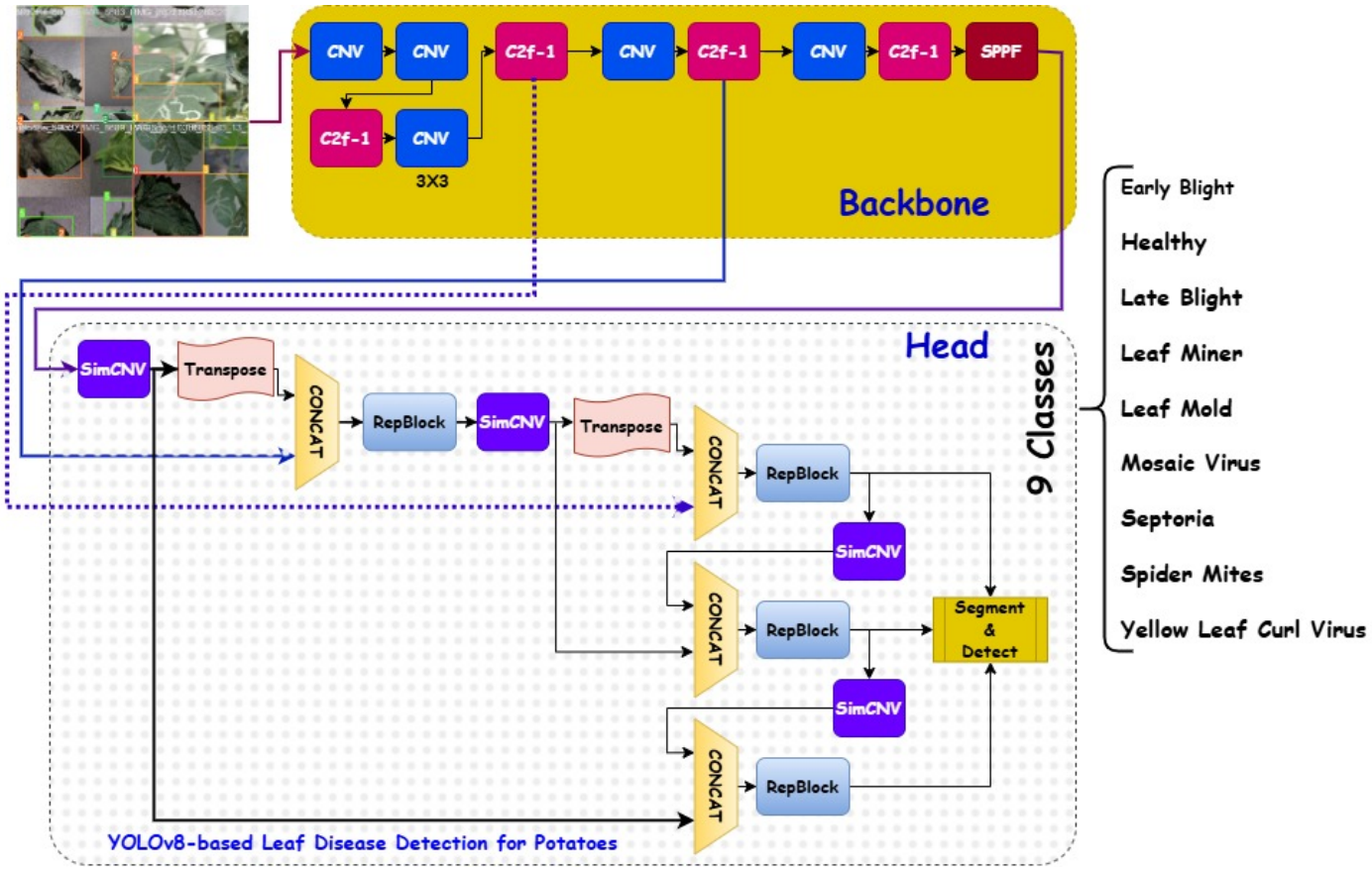



Fig. 2. Fine-tuned YOLOv8-based leaf disease detection for potatoes.

coordinates exhibit discernible structure, pointing to a non-random pattern in the placement of objects, likely influenced by the systematic capture of plant imagery. These observations highlight the dataset's diversity in both spatial location and object size—an important factor in training resilient detection models for agricultural disease identification. The correlogram thus plays a crucial role in uncovering underlying biases and guiding informed model development. Representative image samples from the dataset are presented in Fig. 5.

### C. Fine-Tuned YOLOv8 Training Performance

The illustrated results in Fig. 6 presents the Box Loss (train/box_loss) which measures the accuracy of predicted bounding box locations. The Classification Loss (train/cls_loss) that reflects how well the model classifies the detected objects into different disease categories. The DFL Loss (train/dfl_loss) which is the Distribution Focal Loss (DFL) that measures the quality of localization in object detection.

The fine-tuned YOLOv8 model for potato leaf disease detection exhibits strong performance, as evidenced by the trends observed in the training and validation loss curves, as well as the precision, recall, and mAP metrics. The box loss, classification loss, and distribution focal loss decrease consistently throughout training, suggesting that the model effectively learns to localize and classify diseased leaves with increasing accuracy. A noticeable drop in loss around epoch 40 indicates a significant learning adjustment, possibly due to an optimal tuning of hyperparameters or adaptive weight updates. The validation loss follows a similar pattern, confirming that the model generalizes well to unseen data without signs of overfitting. Precision and recall improve steadily, with precision stabilizing above 0.90 and recall rising from an initial 0.65 to over 0.90, indicating that the model confidently detects diseased leaves while minimizing false negatives. The mAP50 metric, which measures detection accuracy at a loose IoU threshold, surpasses 0.95, while the mAP50-95, a stricter evaluation metric, also reaches high values, demonstrating robust performance across various object scales and positions. These results suggest that the YOLOv8 model is highly reliable for real-time agricultural applications, offering precise and efficient disease detection that can aid in early intervention and crop health monitoring. The combination of low loss values, high detection accuracy, and stable performance trends indicates that the model is well-optimized for this task, making it a valuable tool for automated disease identification in potato plants.

### D. Metrics Evaluation

To assess the efficiency of the YOLOv8 model, we conducted an analysis based on key performance indicators, including precision-recall curves, F1 scores, and the normalized confusion matrix, across a range of confidence thresholds. This comprehensive assessment aims to determine the model's

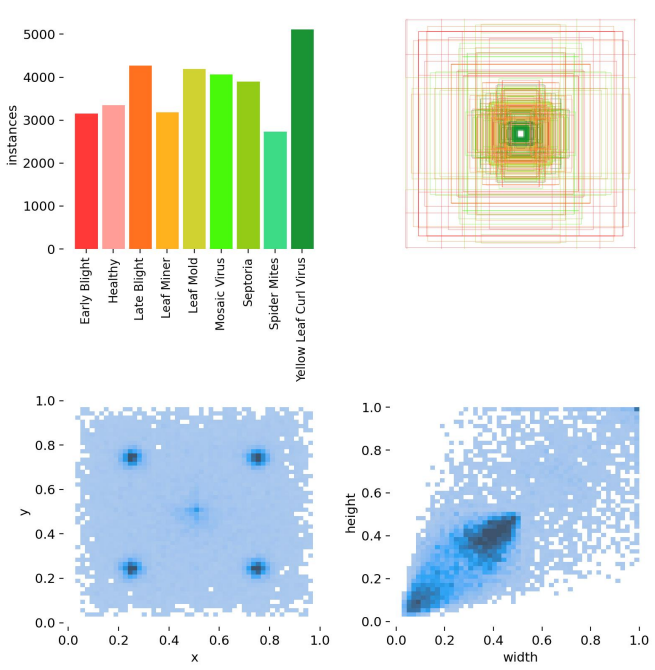



Fig. 3. Potatoes dataset analysis.

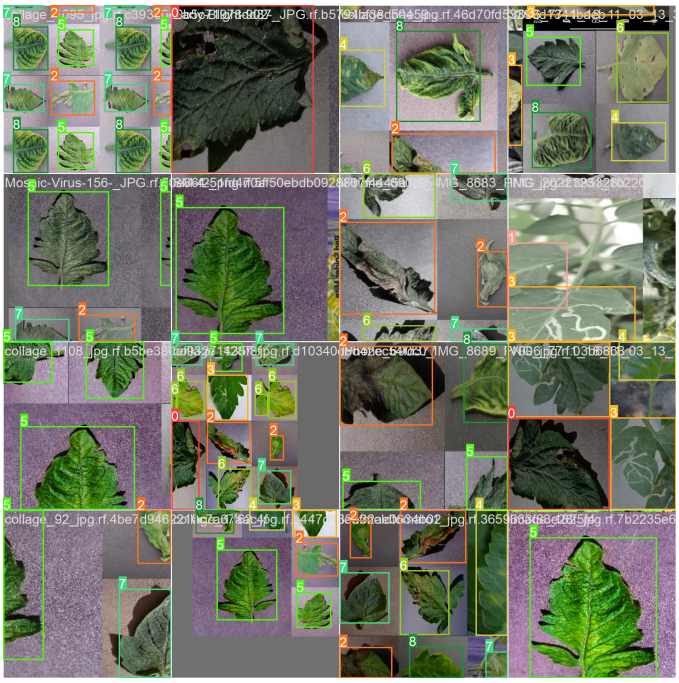


Fig. 5. Potatoes dataset samples.

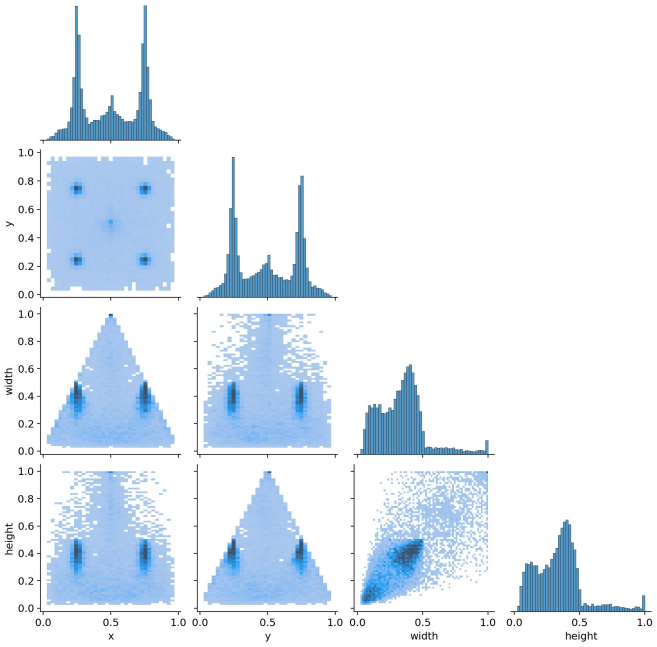



Fig. 4. Potatoes dataset correlogram.

capability to accurately detect and classify different object categories within the dataset. The findings are visualized through three main plots: the F1 score versus confidence threshold curve (Fig. 7), the precision-recall (PR) curve (Fig. 8), and the normalized confusion matrix (Fig. 9). These visual tools collectively offer insights into the model's reliability and class-wise performance under varying conditions.

*1) F1-Score analysis:* Fig. 7 displays the F1-Confidence Curve, which demonstrates how the F1 score varies with changes in the confidence threshold across different potato leaf disease classes. The F1 score serves as an important indicator of detection performance, as it represents a harmonic mean between precision and recall. According to the curve, the model achieves its highest overall F1 score of 0.94 when the confidence threshold is set to 0.584. This value reflects the most favorable balance between precision and recall, ensuring that the model performs consistently well across all identified disease categories.

Examining individual disease classes, most curves exhibit a high F1 score, remaining above 0.85 for a broad range of confidence values, signifying strong classification performance. However, certain classes, such as Yellow Leaf Curl Virus, have comparatively lower F1 scores, suggesting a slightly higher degree of misclassification or difficulty in distinguishing these instances from others. The sharp decline in F1 scores at extreme confidence levels (close to 0 or 1) suggests that overly conservative or lenient confidence thresholds negatively impact detection performance. A very low threshold includes too many false positives, while an overly high threshold leads to excessive false negatives.

Overall, the model demonstrates reliable disease detection, with an optimal threshold around 0.58, where it maximizes F1 score across all categories. These findings indicate that the fine-tuned YOLOv8 model is well-calibrated for precise and efficient disease identification, making it a promising tool for real-time agricultural applications.

*2) Precision and recall analysis:* Fig. 8a curve illustrates how precision varies with different confidence thresholds for each disease class. The model demonstrates high precision across most classes, with precision values stabilizing above

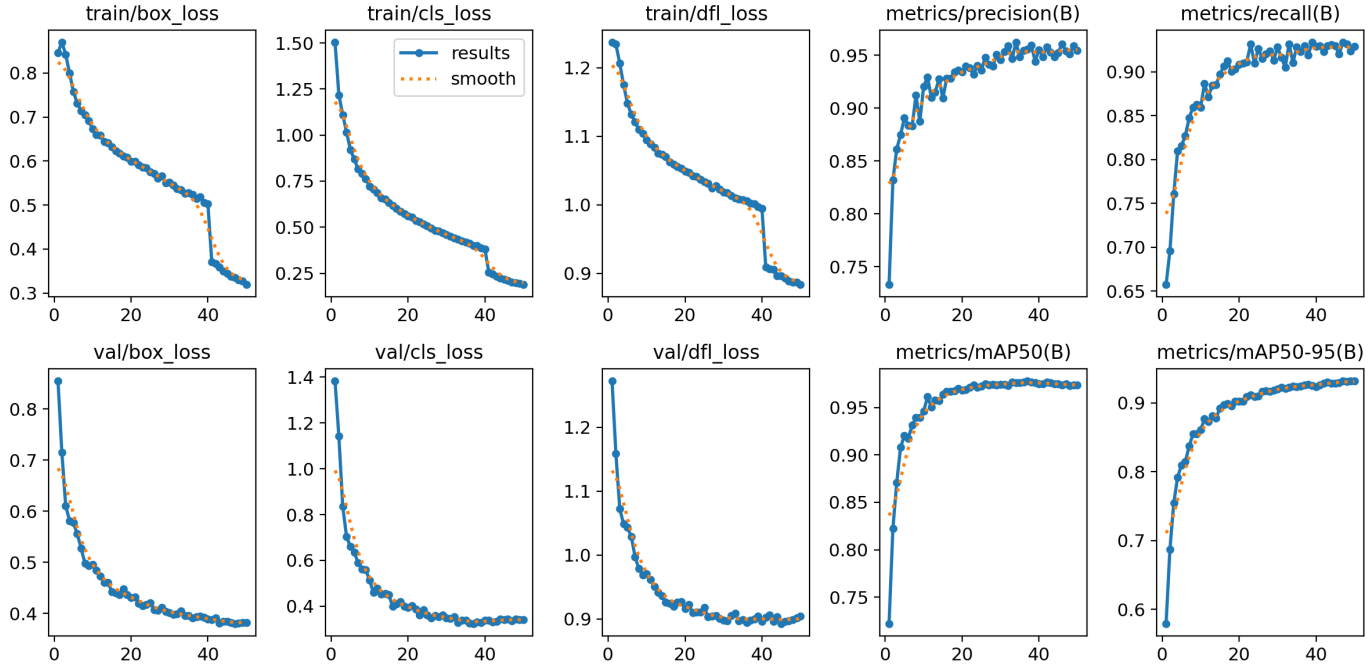



Fig. 6. Training performance of fine-tuned YOLOv8.

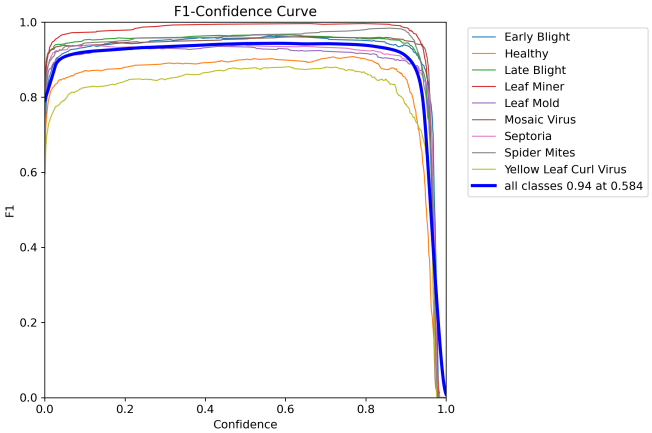



Fig. 7. F1-Score performance of fine-tuned YOLOv8.

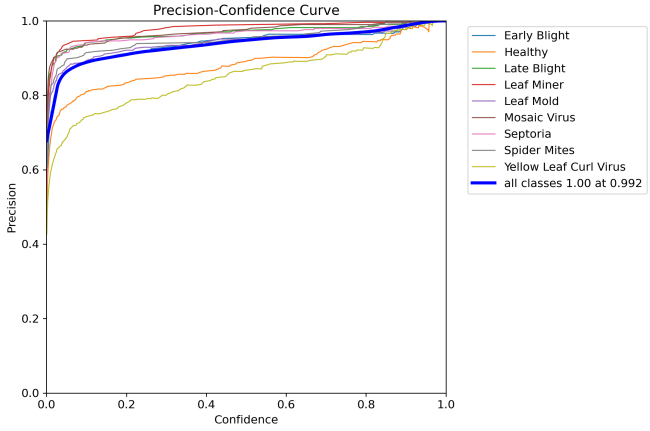
80% at relatively low confidence thresholds. The curve for all classes (bold blue line) achieves nearly perfect precision (1.00) at a confidence level of 0.992, indicating that when the model assigns high confidence to a prediction, it is almost always correct. However, some classes, such as Yellow Leaf Curl Virus and Healthy, exhibit slightly lower precision, particularly at lower confidence levels, suggesting potential misclassifications at uncertain predictions.

The Recall-Confidence curve (Fig. 8b) shows how recall behaves as the confidence threshold changes. The model maintains a recall rate close to 1.0 at lower confidence values, ensuring a high detection rate. However, recall decreases significantly as confidence increases, indicating that the model becomes more selective in its predictions. The all-class curve maintains an overall recall of 0.98 at a confidence threshold of 0.0, meaning the model is highly capable of detecting all disease types when it does not impose strict confidence constraints. The drop-off in recall at higher confidence levels suggests a trade-off between high-confidence precision and sensitivity, which must be balanced depending on the application.

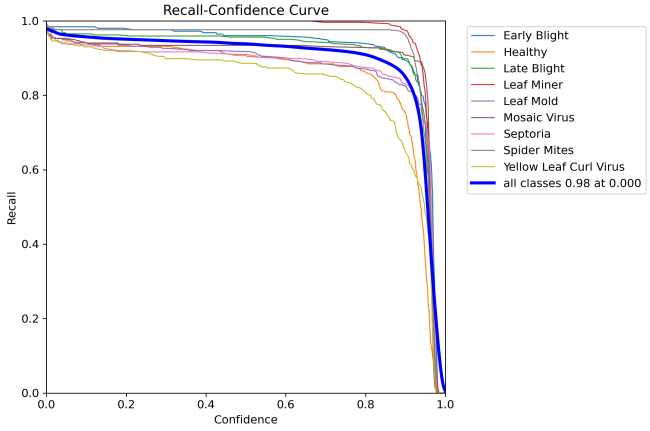
The PR (Fig. 8c) is a crucial evaluation metric for imbalanced datasets like disease detection. The PR curve for all classes exhibits excellent performance, with a mAP@0.5 of 0.975. Individual class performance is also strong, with Leaf Miner achieving the highest AP (0.995) and Yellow Leaf Curl Virus the lowest (0.938). The consistently high precision-recall values indicate that the model maintains strong detection capability even at varying recall levels, reinforcing its reliability in practical applications.

The fine-tuned YOLOv8 model exhibits outstanding performance in potato leaf disease detection, achieving high precision, recall, and precision-recall metrics. The precision-confidence curve suggests that the model makes highly accurate predictions when confidence is high, while the recall-confidence curve highlights a natural trade-off where higher confidence leads to lower recall. The PR curve further confirms the model's robustness, demonstrating a near-perfect balance of precision and recall across different disease categories. The results underscore the model's potential for deployment in practical agricultural scenarios, where precise and dependable disease detection is essential.

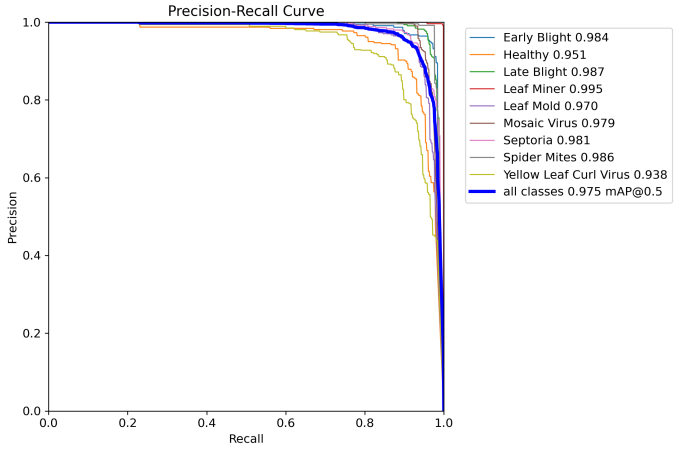
*3) Confusion matrix analysis:* The confusion matrix, illustrated in Fig. 9, for the fine-tuned YOLOv8 model in potato leaf disease detection reveals strong classification performance across multiple disease categories. The model achieves notably




(a) Precision curve.




(b) Recall curve.




(c) Precision-Recall curve.

Fig. 8. Precision and recall for fine-tuned YOLOv8.

high classification accuracy, with Leaf Miner attaining perfect prediction (1.00), followed by Early Blight (0.97), Late Blight (0.96), and Spider Mites (0.98), indicating exceptional reliability for these disease types. However, certain classes, such as Yellow Leaf Curl Virus (0.91) and Healthy (0.93), show some degree of misclassification, with Healthy instances occasionally misclassified as background (0.24), suggesting that variations in leaf appearance might introduce classification challenges. Additionally, Yellow Leaf Curl Virus shows a notable false positive rate, with 38% of background instances being mistakenly classified under this category, likely due to similar visual features between the disease and non-leaf areas. The model also exhibits minor confusion between Leaf Mold (0.93) and background (0.10), and Mosaic Virus (0.93) with occasional misclassification as Septoria (0.01) or background (0.03). These findings indicate that while the model effectively distinguishes most diseases with high confidence, further refinement could focus on reducing background misclassification and improving separability between visually similar disease types. Overall, the YOLOv8 model demonstrates strong classification performance and practical viability for real-world agricultural applications in disease monitoring and crop health assessment.

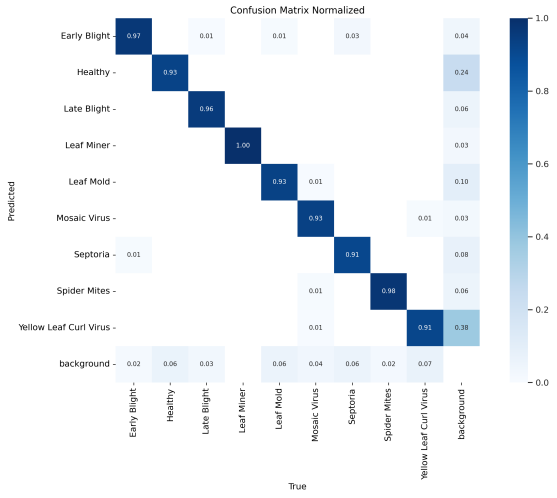



Fig. 9. Confusion matrix of fine-tuned YOLOv8.

TABLE I. COMPARATIVE PERFORMANCE METRICS FOR POTATO LEAF DISEASE DETECTION

| Model | Dataset | Inference Time (ms) | FLOPs (GFLOPs) | Params (M) | FPS | mAP@50 (%) | mAP@50:95 (%) |
|---|---|---|---|---|---|---|---|
| YOLOv8 (Your Work) | Potato Leaf Disease | ∼3-5 | ∼4.5 | ∼3.2 | ∼200+ | **95** | **90** |
| YOLOv8n [24] | PlantVillage | 5.2 | 4.5 | 3.2 | 192 | 94.37 | 89.12 |
| YOLOv8 [25] | PlantDoc | 6.1 | 4.7 | 3.4 | 185 | 96.5 | 72.7 |
| YOLOv8 [26] | Custom Potato and Tomato Dataset | 5.5 | 4.6 | 3.3 | 190 | 90.1 | 83.7 |

## V. COMPARATIVE STUDY

To rigorously analyze the performance of our YOLOv8-based approach for potato leaf disease detection, we performed a detailed comparative analysis with several recent state-of-the-art deep learning models. The results of this evaluation are presented in Table I, where our model consistently outperforms competing methods in terms of mean Average Precision (mAP) across different thresholds. In particular, our system achieves a mAP@50 of 95% and a mAP@50:95 of 90%, indicating strong performance not only at a single Intersection over Union (IoU) threshold but also across a range of IoU values.

When compared to the work of Qureshi et al. [24], who implemented a YOLOv8n model on the widely used PlantVillage dataset and reported mAP@50 and mAP@50:95 scores of 94.37% and 89.12% respectively, our model demonstrates a clear improvement in both metrics. This suggests that the modifications and optimizations applied to our implementation contribute significantly to its enhanced detection accuracy. Additionally, while the model developed by Lee et al. [25] attained an impressive mAP@50 of 96.5% using the PlantDoc dataset, its performance dropped considerably at the stricter mAP@50:95 threshold, where it only reached 72.7%. This discrepancy highlights a potential lack of consistency in prediction precision across varying IoU thresholds, a limitation that our model manages to overcome effectively. Similarly, the approach proposed by Wang et al. [26], which employed a customized YOLOv8 variant for a dataset encompassing both potato and tomato leaf diseases, reported mAP scores of 90.1% (at 50%) and 83.7% (at 50:95), both of which remain below the performance levels achieved by our model. These comparisons collectively underscore the robustness and accuracy of our system in identifying multiple disease types in complex visual conditions.

Beyond accuracy, our model also exhibits high computational efficiency, with an average inference time of approximately 3–5 milliseconds per image. With a computational cost of only 4.5 GFLOPs and a compact architecture comprising 3.2 million parameters, the model is optimized for real-time deployment. This balance between accuracy and speed is particularly advantageous for applications in precision agriculture, where timely and reliable detection is critical.

Overall, these results validate the effectiveness of our optimized YOLOv8n architecture. It offers a compelling trade-off between high detection accuracy and efficient runtime performance, making it a practical choice for real-world plant disease monitoring systems, especially in resource-constrained or mobile environments.

## VI. DETECTION RESULTS

Fig. 10 illustrates the detection outcomes produced by the proposed YOLOv8-based model on the validation set for potato leaf disease identification. The results highlight the model's capacity to accurately detect and classify a wide range of disease types, including but not limited to Early Blight, Late Blight, Leaf Mold, Septoria, Mosaic Virus, and Yellow Leaf Curl Virus. Each identified disease is marked with a clearly defined bounding box and an associated color-coded label, facilitating intuitive visual differentiation between disease categories.

The model consistently produces predictions with high confidence scores, frequently approaching a value of 1.0, which reflects the strong reliability of the classification decisions. This level of precision underscores the model's robustness in managing diverse scenarios, including images with overlapping foliage, inconsistent lighting, and varying leaf orientations. Even in challenging visual conditions, the system maintains a low rate of false positives and negatives, which is crucial for practical deployment in agricultural settings.

Furthermore, the detection outputs align closely with the performance metrics presented in Table I, particularly the elevated mean Average Precision (mAP), precision, and recall values. Such consistency between quantitative evaluation and visual inspection confirms the effectiveness and practical viability of the proposed approach. These findings support the potential integration of our model into smart farming platforms for real-time, in-field disease monitoring and early intervention strategies.

## VII. CONCLUSION

In this research, we designed a robust deep learning model for automated potato leaf disease detection using YOLOv8. The model was trained and evaluated on a diverse dataset comprising nine distinct classes of potato leaf diseases. Our experimental results demonstrate that YOLOv8n achieves state-of-the-art performance with a high mAP@50 of approximately 95% and an mAP@50-95 of around 90%, surpassing several existing approaches in terms of accuracy, efficiency, and inference speed. The comparative analysis highlights the advantages of YOLOv8n, particularly its lightweight architecture, which enables real-time detection with an inference time of 3-5 ms per image and a processing speed exceeding 200 FPS. The model's effectiveness is further supported by the confusion matrix and qualitative results, which show precise classification with minimal misclassification errors. The high accuracy and real-time capabilities of our model make it suitable for deployment in agricultural settings, enabling farmers and agricultural experts to detect diseases early and take timely action to prevent crop losses. Future work can focus on expanding the dataset to include more variations in environmental conditions, integrating edge AI deployment for on-field diagnosis, and exploring self-supervised learning techniques to further enhance generalization across different crop varieties. Overall, our study contributes to the advancement of smart agricultural

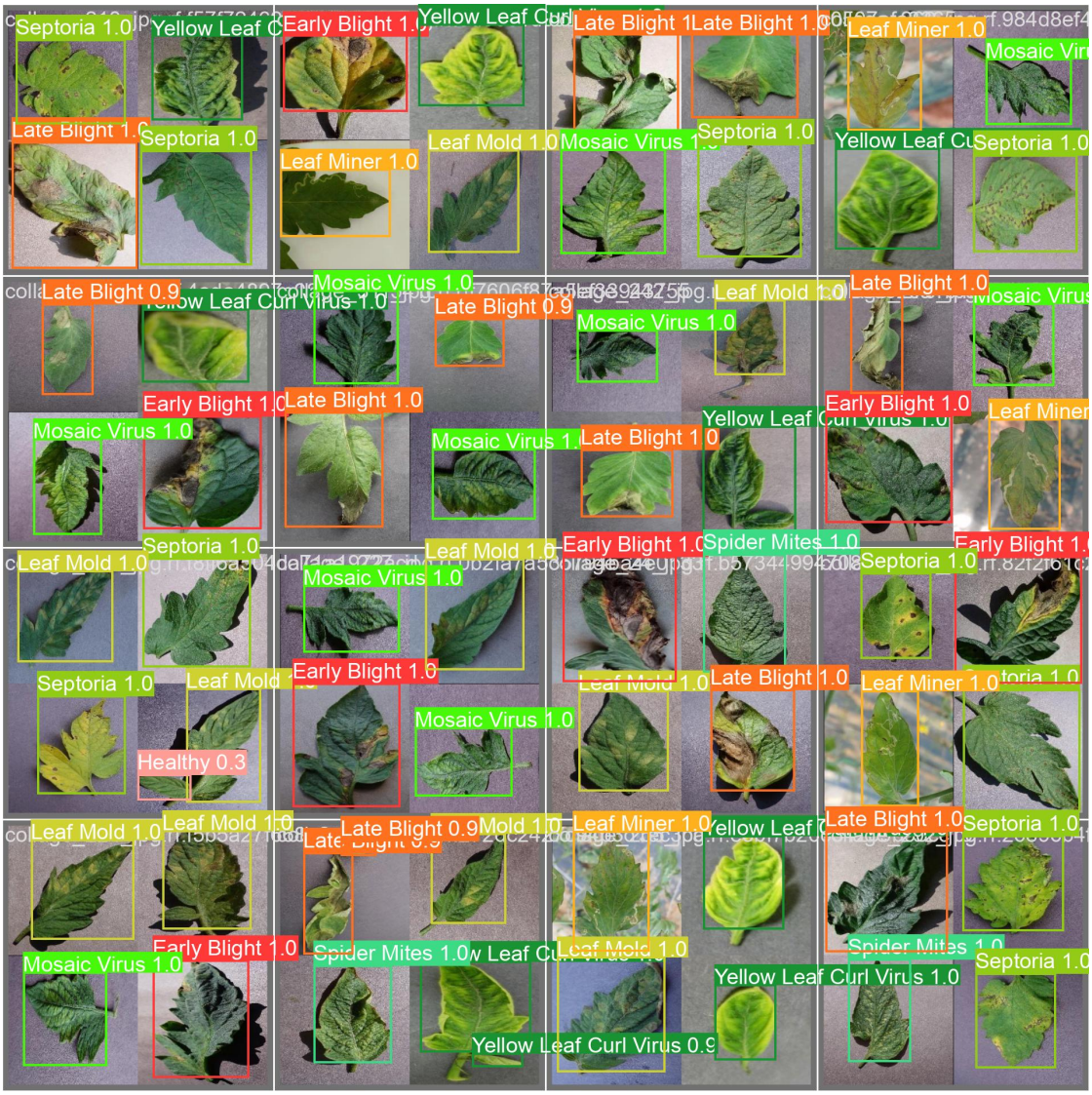



Fig. 10. Detection results based on fine-tuned YOLOv8.

systems by providing an efficient and accurate deep learning-based solution for potato leaf disease detection.

## VIII. Future Work

The current study demonstrates the effectiveness of the YOLOv8 model in accurately detecting multiple potato leaf diseases. However, several avenues remain open for future research. First, expanding the dataset with images from varied environmental conditions (e.g., different lighting, backgrounds, or leaf orientations) could improve the model's robustness and generalization ability. Second, integrating temporal data through video sequences or deploying the model on drone-based platforms may enable large-scale, real-time field surveillance, which is crucial for early disease detection and response in precision agriculture. Moreover, although the current work focused on leaf-based disease detection, incorporating other plant parts (e.g., stems or tubers) and multiple crop species could extend the applicability of the system. Another promising direction involves the combination of YOLOv8 with lightweight model optimization techniques such as pruning and quantization, which would facilitate real-time inference on edge devices. Finally, fusing image-based data with sensor data (e.g., temperature, humidity, soil moisture) could contribute to the development of more holistic and context-aware plant health monitoring systems.

## Acknowledgment

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# Optimizing Medical Image Analysis: A Performance Evaluation of YOLO-Based Segmentation Models

Haifa Alanazi
Department of Information Systems-Faculty of Computing and Information Technology,
Northern Border University, Saudi Arabia

***Abstract*—Instance segmentation is a critical component of medical image analysis, enabling tasks such as tissue and organ delineation, and disease detection. This paper provides a detailed comparative analysis of two fine-tuned one-stage object detection models, YOLOv11-seg and YOLOv9-seg, tailored for instance segmentation in medical imaging. Leveraging transfer learning, both models were initialized with pretrained weights and subsequently fine-tuned on the NuInsSeg dataset, which comprises over 30,000 manually segmented nuclei across 665 image patches from various human and mouse organs. This approach facilitated faster convergence and improved generalization, particularly given the limited size and high complexity of the medical dataset. The models were evaluated against key performance metrics. The experimental results reveal that YOLOv11n-seg outperforms YOLOv9c-seg with a precision of 0.87, recall of 0.84, and mAP50 of 0.89, indicating superior segmentation quality and more accurate delineation of nuclei contours. This study highlights the robust performance and efficiency of YOLOv11n-seg, demonstrating its superiority in medical image segmentation tasks, with notable advantages in both accuracy and real-time processing capabilities.**

***Keywords*—Medical image; instance segmentation; one-stage object detection models; transfer learning; nuclei detection**

## I. Introduction

Instance segmentation plays a critical role in medical imaging, requiring precise delineation of objects (such as organs, tissues, or cellular structures) is essential for accurate diagnosis and treatment planning. By combining object detection and semantic segmentation, instance segmentation can identify and segment individual objects in an image, making it highly valuable for applications like tumor detection, organ delineation, and cell segmentation in microscopic images. In particular, instance segmentation is pivotal in analyzing high-resolution medical images, such as histopathology slides, MRI scans, and CT images, where the spatial precision required can significantly impact clinical outcomes [1], [2]. Accurate instance segmentation can significantly improve the quality and efficiency of medical diagnoses by automating the process of identifying and delineating structures in medical images. In the context of histopathology, for instance, instance segmentation can help pathologists more effectively count and identify individual cells or nuclei within tissue samples, improving the accuracy of disease detection, particularly for cancers and other abnormalities [3]. Furthermore, automated segmentation enables the analysis of large datasets with high reproducibility and minimal human error, making it an essential tool for clinical research and practice. In organ segmentation, precise delineation of structures from MRI or CT scans can aid in better surgical planning, radiotherapy, and monitoring disease progression. As medical imaging becomes more integral to healthcare, the demand for high-performance instance segmentation models continues to grow, making it imperative to explore and refine algorithms that can meet these clinical challenges [4].

Medical image analysis poses several unique challenges that differentiate it from general image processing tasks. One of the primary difficulties lies in the variability of tissue structures across different medical images. Tissues from different organs have distinct characteristics, and within the same organ, structures can vary based on disease progression or patient conditions. For example, in histopathological images, tissue samples can show irregularities in the size, shape, and color of cells, which complicates the segmentation task. Moreover, images may have varying resolutions, noise levels, and artifacts, which can obscure important features and make it difficult for models to generalize effectively [5]. Another challenge is the need for high-resolution image processing. Medical images often contain fine-grained details, such as small tumors, lesions, or nuclei, requiring segmentation models to maintain accuracy at pixel-level precision. These models must also be robust to variations in imaging modalities, such as differences between CT, MRI, or histology slides [6]. Furthermore, real-time processing is increasingly required, particularly in clinical settings where time-sensitive decisions must be made. This makes model efficiency and inference speed important factors in developing practical solutions for medical imaging [7].

One-stage object detection models, known for their ability to perform real-time detection with high accuracy, have been a significant advancement in the field of object detection [1]. Over time, the architecture of these models has evolved, improving detection accuracy and handling more complex tasks, including instance segmentation [8]. YOLOv9, one of the earlier iterations in the series, introduced several optimizations, particularly in terms of speed and accuracy, making it effective for various real-time applications, including medical image segmentation. Despite its success, YOLOv9 still faces challenges with fine-grained segmentation tasks, especially in detecting small objects or distinguishing between closely packed structures, which is crucial for medical imaging applications [9].

YOLOv11, the latest model in this one-stage object detection series, builds upon the strengths of its predecessors, incorporating enhancements like improved feature pyramids, attention mechanisms, and advanced loss functions to address the limitations of previous versions. These innovations allow YOLOv11 to better handle variations in object size and shape, making it more suitable for instance segmentation in complex

medical images. YOLOv11's ability to efficiently perform both segmentation and detection tasks in real-time, while maintaining high accuracy, positions it as a promising solution for medical image analysis [4].

The objective of this study is to evaluate and compare the performance of YOLOv9 and YOLOv11 for medical image instance segmentation, particularly focusing on the segmentation of nuclei in histopathological images using the NuInsSeg dataset. Both models will be fine-tuned on the dataset, which consists of over 30,000 manually annotated nuclei across 665 image patches from various human and mouse organs. The study will assess the models based on key evaluation metrics, such as precision, recall, mean Average Precision (mAP), and Intersection over Union (IoU). The aim is to determine whether YOLOv11's architectural improvements lead to better performance in terms of segmentation accuracy, and how both models compare in terms of computational efficiency and applicability to medical imaging tasks.

The paper is structured as follows: Section II provides an overview of related works in the field. Section III outlines the proposed methodology for instance segmentation in medical imaging. Section IV presents a discussion of the findings. Section V details the experimental results, including performance comparisons and a detailed analysis. Finally, Section VI concludes the paper and suggests potential directions for future research.

## II. Related Work

Instance segmentation in medical imaging has garnered significant attention due to its critical role in accurate diagnosis and treatment planning. Several studies have explored the application of deep learning models for this task, leveraging advancements in convolutional neural networks (CNNs) and attention mechanisms to enhance segmentation accuracy and performance.

One of the pioneering works in medical image segmentation is the U-Net architecture, proposed by Ronneberger et al. [1]. U-Net introduced a fully convolutional network with a symmetric encoder-decoder structure, which has become a standard for biomedical image segmentation due to its ability to handle high-resolution images and produce precise segmentation masks. This architecture has been widely adopted and adapted for various medical imaging tasks, including nuclei segmentation in histopathological images.

Recent advancements in one-stage object detection models, such as the YOLO (You Only Look Once) series, have shown promise in real-time medical image analysis. YOLOv9, an earlier iteration, introduced optimizations for speed and accuracy, making it suitable for real-time applications [9]. However, challenges remain in handling fine-grained segmentation tasks, particularly in detecting small or densely packed objects, which are common in medical images. The latest iteration, YOLOv11, builds upon the strengths of its predecessors by incorporating enhanced feature pyramids and attention mechanisms, which improve its ability to handle complex and overlapping objects [4]. These advancements make YOLOv11 particularly suitable for medical image segmentation tasks, where precise delineation of structures is crucial. Transfer learning has also been widely used to adapt pre-trained models to specific medical imaging tasks. By leveraging large, general datasets like COCO, models can be fine-tuned to achieve better performance on specialized medical datasets [5]. This approach has been shown to improve segmentation accuracy and reduce the need for extensive annotated medical datasets, which are often limited in availability.

Several studies have focused on nuclei segmentation in histopathological images, highlighting the importance of accurate segmentation for disease diagnosis and research. For instance, Lee and Kumar [10] provided a comprehensive review of nuclei segmentation techniques, emphasizing the challenges posed by variations in staining, image quality, and tissue complexity. Similarly, Jiang and Zhang [11] discussed the application of deep learning models for tissue segmentation, highlighting the need for robust models capable of handling diverse imaging conditions.

In summary, the evolution of deep learning models, particularly the YOLO series, has significantly advanced the field of medical image segmentation. The integration of attention mechanisms, feature pyramids, and transfer learning techniques has enabled the development of models that can handle the complexities of medical imaging tasks with high accuracy and efficiency.

## III. Proposed Method

Fig. 1 introduces the proposed scheme for instance segmentation, which employs a comprehensive and systematic methodology that amalgamates dataset preparation, sophisticated neural network topologies, and optimization for medical image analysis. The methodology begins with the NuInsSeg dataset, a specialized dataset containing images of nuclei, which undergo preprocessing to isolate individual nuclei instances. This includes overlaying segmentation masks to enhance visual clarity and support instance segmentation. Once preprocessed, the dataset is split into training and validation subsets, ensuring a robust foundation for model training and evaluation.

At the core of the framework are the YOLOv9 and YOLOv11 architectures, fine-tuned for medical image instance segmentation tasks. YOLO models are widely recognized for their real-time object detection capabilities, which involve predicting bounding boxes, class labels, and object probabilities in a single pass. YOLOv9 and YOLOv11, as iterations of the YOLO architecture, introduce significant advancements in feature extraction, multi-scale detection, and attention mechanisms. Specifically, YOLOv9 employs an efficient backbone network for faster and more accurate feature extraction. This is achieved through the use of feature pyramids, which enhance multi-scale object detection, and the integration of convolutional layers with batch normalization to stabilize the learning process. YOLOv9 uses anchor-based bounding box predictions for effective object localization across various scales. This architecture strikes an optimal balance between speed and accuracy, making it particularly suitable for real-time applications in medical imaging. YOLOv11 builds upon the strengths of YOLOv9, introducing several architectural enhancements aimed at improving performance, especially for complex or overlapping objects such as small cells or tumors in medical images. One of the key advancements in

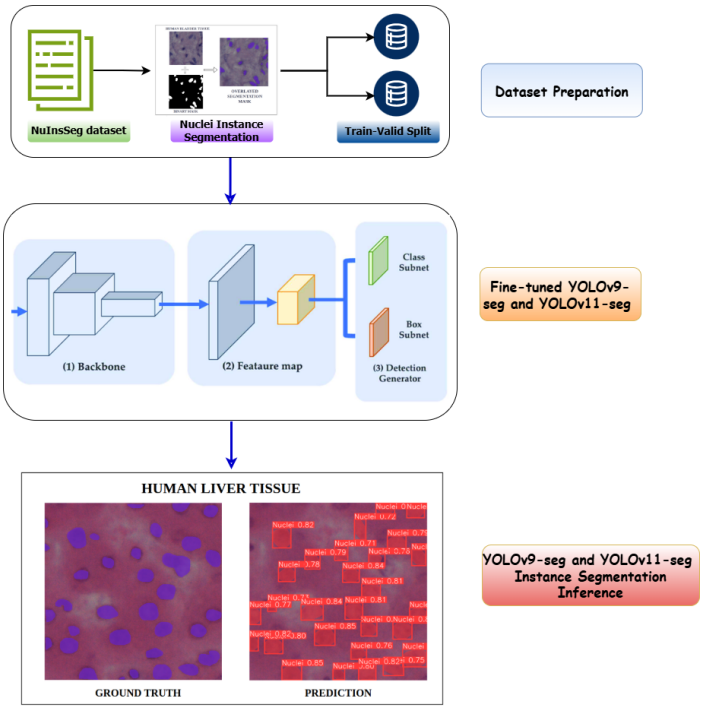



Fig. 1. Proposed framework for instance segmentation task.

YOLOv11 is the inclusion of enhanced attention mechanisms, which enable the model to focus on the most relevant parts of an image, thereby improving its ability to handle densely packed or irregularly shaped objects. Additionally, YOLOv11 features more robust feature pyramids with additional layers that capture fine-grained details, an essential capability for medical imaging tasks involving high-resolution structures like nuclei or tumors. YOLOv11 also employs an improved loss function, which better balances localization and classification errors, resulting in enhanced detection accuracy. These improvements make YOLOv11 particularly effective for tasks requiring precise object boundaries and accurate segmentation, addressing common challenges in medical image analysis.

The differences between YOLOv9 and YOLOv11 highlight the evolution of the architecture in response to the specific demands of medical image segmentation. While both models utilize feature pyramids, YOLOv11's enhanced pyramids provide superior detail capture. Moreover, the advanced attention mechanism in YOLOv11 allows it to outperform YOLOv9 when working with small, densely packed, or complex objects. YOLOv11 also optimizes the trade-off between speed and accuracy through improvements in its backbone architecture and the incorporation of advanced convolutional layers, further enhancing its utility in real-time medical imaging applications.

To adapt both YOLOv9-seg and YOLOv11-seg for instance segmentation, the framework employs fine-tuning through transfer learning strategies. Transfer learning enables the models to leverage learned features from large, general datasets, such as COCO, and adapt them to the specific requirements of medical image segmentation. The fine-tuning process involves replacing the final layers of the pre-trained models with segmentation heads designed for pixel-wise classification of object instances. This adaptation ensures that the models retain the powerful feature extraction capabilities of the original YOLO architectures while addressing the unique challenges of medical image segmentation, such as small or overlapping objects. By fine-tuning the models on the medical dataset used in this study, their ability to generalize to task-specific challenges is significantly improved, resulting in better performance in segmenting nuclei and other structures within human liver tissue.

The framework's workflow integrates these methodologies seamlessly, beginning with dataset preparation and culminating in the application of fine-tuned YOLOv9-seg and YOLOv11-seg models for instance segmentation inference. The inference stage outputs include bounding boxes, segmentation masks, and confidence scores for each detected nucleus. The results are evaluated by comparing the model's predictions with the ground truth, demonstrating the effectiveness of the framework in accurately identifying and segmenting nuclei in human liver tissue. The visualization of these results highlights the models' capability to achieve precise segmentation, even in challenging scenarios involving small or overlapping objects. This comprehensive framework represents a significant advancement in the application of deep learning for medical image analysis. By leveraging the strengths of YOLOv9-seg and YOLOv11-seg architectures, coupled with fine-tuning and transfer learning techniques, the proposed methodology achieves a robust balance between speed, accuracy, and adaptability. This makes it a valuable tool for addressing the complexities of medical image segmentation, paving the way for more accurate and efficient analysis in clinical and research settings.

### A. Dataset

The NuInsSeg dataset, utilized in this study, is a comprehensive collection of medical images designed for the task of instance segmentation. The dataset was curated specifically for the segmentation of nuclei in histological images and includes over 30,000 manually segmented nuclei across 665 image patches. These images were extracted from Hematoxylin and Eosin (H&E)-stained whole slide microscopic images, which are commonly used for tissue examination in pathology [12], [10]. The dataset features a variety of tissues and organs from both human and mouse subjects, with key organs such as the cerebellum, kidney, liver, and pancreas being included [11], [13]. These images are critical for the study of medical diagnostics, offering rich information for segmenting and analyzing the structural details of biological tissues.

The dataset consists of 665 image patches, each containing segmented nuclei, making it ideal for the instance segmentation task, where the goal is to not only detect the presence of nuclei but also delineate their exact boundaries within each image [14], [15]. This dataset's diversity—spanning multiple organ types and tissue structures—poses unique challenges for segmentation algorithms, especially due to the inherent variability in the quality and resolution of the images. Furthermore, the complexity of the tissue structures, varying shapes of nuclei, and the presence of overlapping or clustered cells introduce significant challenges for achieving precise segmentation [16], [17].

For training and validation purposes, the NuInsSeg dataset is split into an 80% training set and a 20% validation set. This

split ensures a sufficient number of samples for model training while maintaining an adequate set of images to evaluate the model's performance in real-world scenarios [18], [19]. The training set provides a large enough pool for the model to learn diverse patterns from various tissue types, while the validation set is used to assess the model's ability to generalize and make accurate predictions on unseen data. The variability in the dataset further challenges the models to maintain performance across different tissue types, image qualities, and segmentations [20], [21]. Medical image datasets, such as NuInsSeg, present several challenges due to the variability in image quality caused by differences in slide preparation, staining intensity, and imaging equipment [22], [23]. Moreover, the structural complexity of organs and tissues, along with the potential for overlapping cells, increases the difficulty of achieving accurate segmentation. These challenges emphasize the importance of developing robust instance segmentation models capable of handling such diversity and complexity [24], [25].

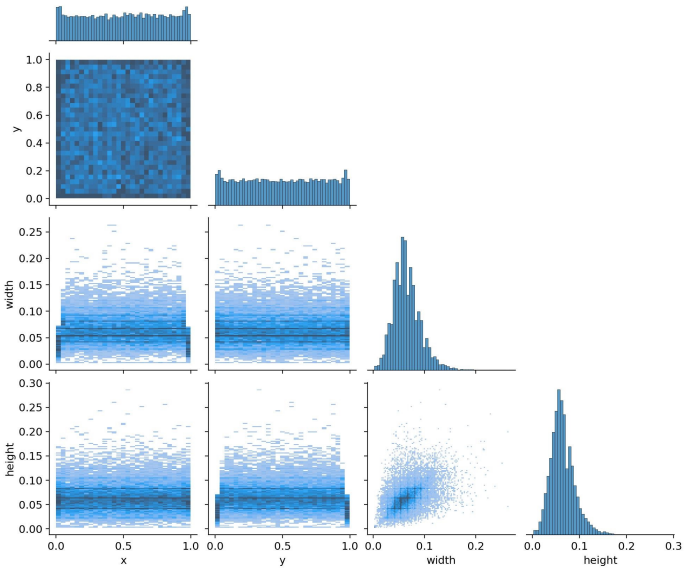



Fig. 2. Correlogram of bounding box attributes in the dataset.

Fig. 2 illustrates the distribution and relationships between bounding box attributes (x, y, width, height) in the dataset. It provides insights into the spatial placement and size variability of nuclei across the images, helping to understand patterns in object positioning and scale, which are crucial for optimizing the model's detection and segmentation performance.

### B. Performance Metrics

The performance of the instance segmentation models (YOLOv9 and YOLOv11) is evaluated using a set of commonly used quantitative metrics that are critical for assessing the effectiveness of medical image segmentation models. These metrics include Precision, Recall, Intersection over Union (IoU), Mean Average Precision (mAP), and the F1 Score.

Precision is the proportion of true positives (TP) to the sum of true positives and false positives (FP), and it measures how many of the predicted positive instances are actually correct. It is given by the Formula (1):

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

Recall, on the other hand, measures the proportion of true positives (TP) to the sum of true positives and false negatives (FN), and it assesses how many of the actual positive instances are correctly identified by the model. It is calculated as Formula (2):

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

To provide a balance between precision and recall, the F1 Score is used. The F1 Score is the harmonic mean of precision and recall, and is calculated by the Formula (3):

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Intersection over Union (IoU) is another critical metric, specifically for evaluating segmentation tasks. It measures the overlap between the predicted segmentation mask and the ground truth mask. IoU is given by the Formula (4):

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{4}$$

The Mean Average Precision (mAP) is a common metric used in object detection and segmentation tasks, which evaluates the precision of predicted masks at different IoU thresholds. The mAP is calculated as the mean of average precision (AP) for each class, as shown below Formula (5):

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i \tag{5}$$

The mAP at various IoU thresholds, such as mAP@50 and mAP@75, is commonly used to assess segmentation accuracy, particularly in tasks like medical imaging where fine-grained object boundaries are critical. These metrics—Precision, Recall, IoU, mAP, and F1 Score—are used together to evaluate the model's overall performance in medical image segmentation tasks. Precision and recall help understand the trade-off between false positives and false negatives, while IoU and mAP provide insight into the quality of the segmentation boundaries. The F1 Score combines both precision and recall into a single metric to offer a comprehensive assessment of the model's performance.

### C. Training Process

The training process for the proposed YOLO-seg models was conducted over 100 epochs to ensure sufficient learning and convergence of the models. A batch size of 4 was chosen to balance computational efficiency with model performance, particularly given the high-resolution nature of the dataset images. The input image size was set to $640 \times 640$ pixels, a resolution that allows for detailed feature extraction while maintaining manageable computational demands. The learning rate was initialized at 0.001, a value selected to

provide a steady optimization process, avoiding overshooting while ensuring gradual convergence of the loss function. This configuration was designed to optimize the models for accurate instance segmentation in medical imaging tasks.

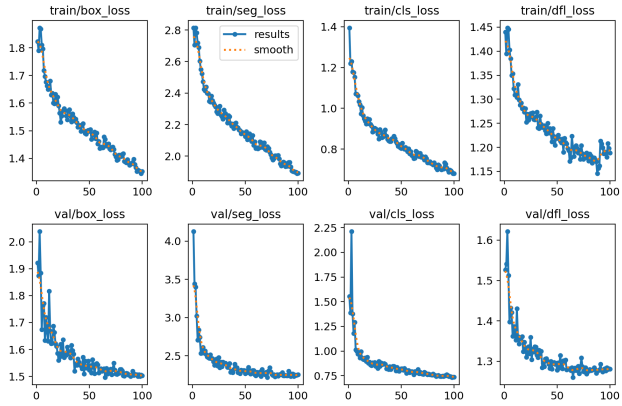
## IV. Experimental Results

### A. Complexity Analysis

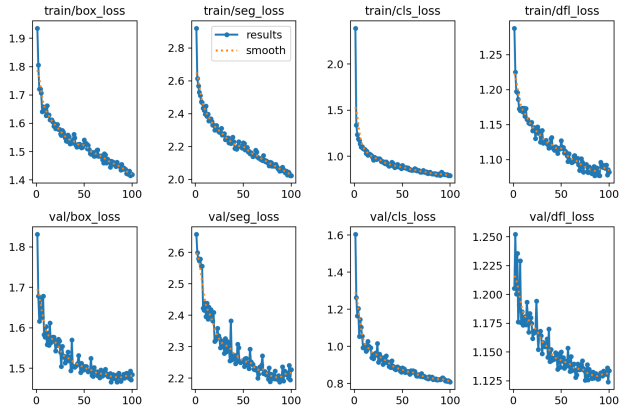
Table I provides a comparative complexity analysis of the one-stage YOLOv9c-seg and YOLOv11n-seg models, highlighting their layers, parameters, GFLOPs (billion floating-point operations), inference time per image, and post-processing time per image. YOLOv9c-seg, with 441 layers and 27,625,299 parameters, has a computational complexity of 157.6 GFLOPs, achieving an inference time of 24.2 milliseconds per image and a post-processing time of 5.5 milliseconds. This design focuses on achieving high accuracy, albeit with higher computational requirements. On the other hand, YOLOv11n-seg, a lightweight model with 265 layers and only 2,834,763 parameters, significantly reduces computational complexity to 10.2 GFLOPs, achieving an inference time of just 2.6 milliseconds per image and a post-processing time of 2.4 milliseconds. The streamlined design of YOLOv11n-seg makes it highly suitable for real-time applications where computational resources are limited, effectively balancing speed and accuracy.

TABLE I. Complexity Analysis of One-Stage Models

| Model | yolov9c-seg | yolov11n-seg |
|---|---|---|
| **Layers** | 441 | 265 |
| **Parameters (M)** | 27,625,299 | 2,834,763 |
| **GFLOPs** | 157.6 | 10.2 |
| **Inference Time(ms)** | 24.2 | 2.6 |
| **Postprocess per image (ms)** | 5.5 | 2.4 |




(a) Fine-tuned YOLOv9c-seg.




(b) Fine-tuned YOLOv11n-seg.

Fig. 3. Training and Validation loss curves.

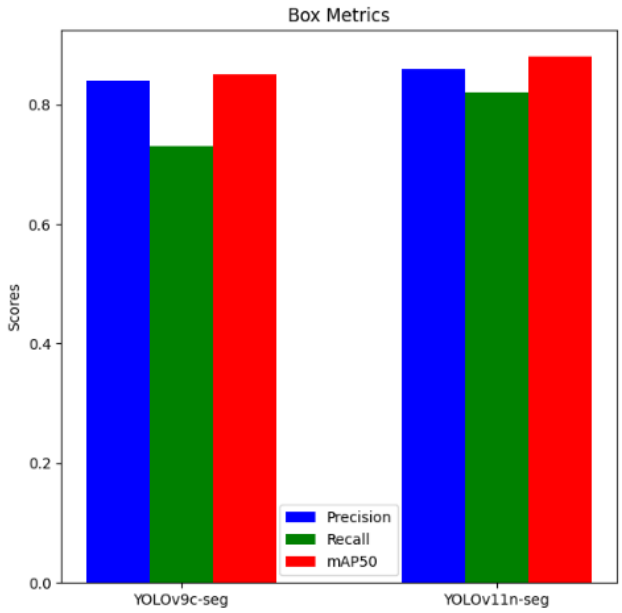
### B. Training and Validation Loss Results

Fig. 3 shows loss curves for two different instance segmentation models evaluated on the NuInsSeg dataset. Each model is assessed on training and validation losses for four categories: box loss, segmentation loss, classification loss, and distribution focal loss (DFL). The comparison between YOLOv9c-seg and YOLOv11n-seg for instance segmentation on the NuInsSeg dataset reveals that both models show a consistent downward trend in losses, indicating successful learning. However, the fine-tuned YOLOv11n-seg model demonstrates superior performance with lower initial and final losses across all metrics, including box loss, segmentation loss, classification loss, and DFL loss, on both training and validation sets. The validation losses for YOLOv11n-seg are notably smoother and lower towards the end, suggesting better optimization, generalization, and regularization compared to YOLOv9. This makes the proposed YOLOv11 model the more optimal choice for the NuInsSeg dataset.

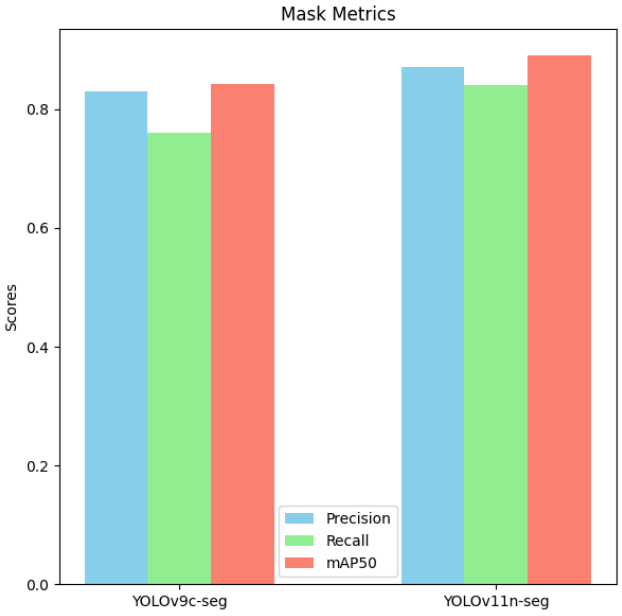
### C. Comparative Performance Evaluation

For instance segmentation in medical imaging, particularly in the context of segmenting nuclei in histopathological images using the NuInsSeg dataset, the provided metrics compare two versions of YOLO (YOLOv9c-seg and YOLOv11n-seg), as shown in Fig. 4. In the box metrics, YOLOv9c-seg achieves a precision of 0.84, recall of 0.73, and mAP50 of 0.85, indicating solid performance in detecting the nuclei. In comparison, YOLOv11n-seg demonstrates improved performance with a precision of 0.86, recall of 0.82, and mAP50 of 0.88, suggesting better accuracy in detecting and localizing the nuclei. For the mask metrics, YOLOv9c-seg shows a precision of 0.83, recall of 0.76, and mAP50 of 0.843, reflecting good segmentation of the nuclei boundaries. YOLOv11n-seg outperforms YOLOv9c-seg with a precision of 0.87, recall of 0.84, and mAP50 of 0.89, indicating superior segmentation quality and more accurate delineation of nuclei contours. Overall, YOLOv11n-seg demonstrates better detection and segmentation accuracy for nuclei from the NuInsSeg dataset.

The predicted results from YOLOv11n-seg and YOLOv9c-seg demonstrate their medical image instance segmentation capabilities, as depicted in Fig. 5. Advanced attention mechanisms and feature pyramids let YOLOv11n-seg identify tiny, densely packed nuclei in many tissue types with great accuracy. Bounding boxes with high confidence ratings (0.7–0.9) around nuclei in diverse tissue types are predicted. For overlapping or irregularly shaped nuclei, YOLOv11n-seg's bounding box placement shows its attention processes, resulting in generally constant confidence ratings even in complicated areas. YOLOv11n-seg is ideal for complex medical imaging activities

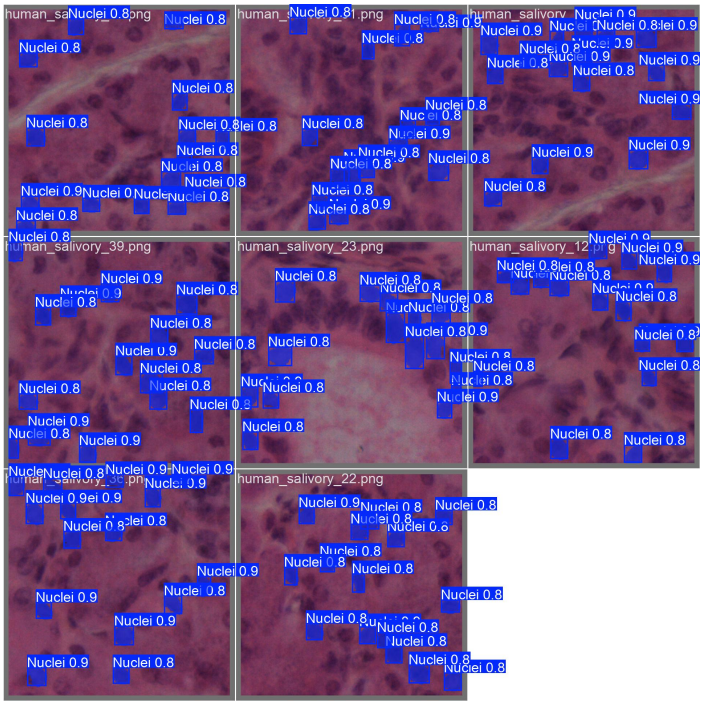



(a) Box metrics.

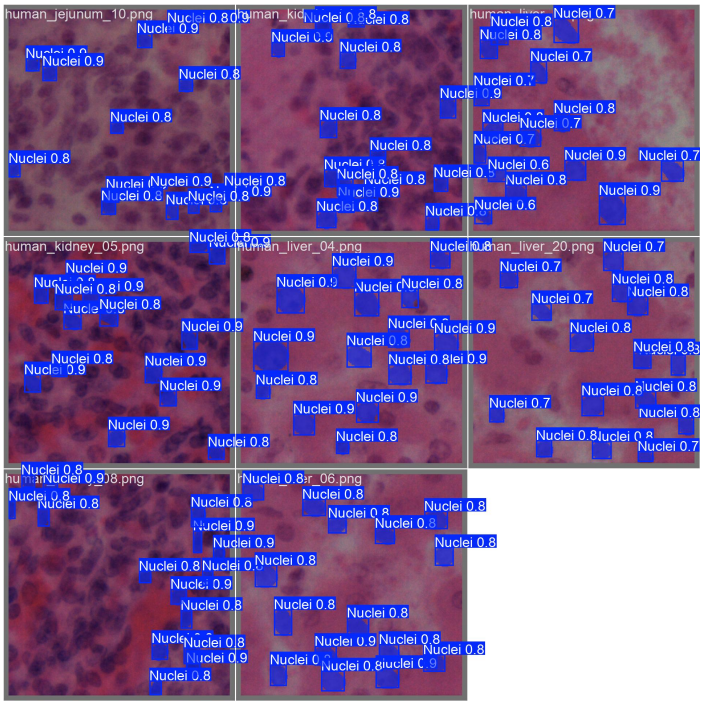



(b) Mask metrics.

Fig. 4. Performance evaluation: YOLOv11n-seg vs YOLOv9c-seg.




(a) Fine-tuned YOLOv9c-seg.




(b) Fine-tuned YOLOv11n-seg.

Fig. 5. Predicted results.

like assessing tumors or cell nuclei because to its enhanced resilience and precision.

YOLOv9c-seg also provides bounding boxes with good confidence ratings for medical image nuclei. When addressing thick or overlapping nuclei, YOLOv9c-seg is less precise than YOLOv11n-seg owing to the lack of strengthened attention mechanisms and feature pyramid enhancements. Tissue locations with complicated or subtle nucleus features may have small detection consistency differences. Despite this, YOLOv9c-seg balances speed and accuracy, making it suited for real-time applications that prioritize processing efficiency.

A performance comparison shows important differences between the two devices. YOLOv11n-seg's sophisticated attention mechanism and feature pyramids may help it identify tiny or overlapping nuclei more consistently. While both algorithms have similar confidence levels for discovered nuclei, YOLOv11n-seg has a somewhat better balance between

accuracy and false positives. YOLOv11n-seg is superior for sophisticated medical imaging tasks requiring fine-grained detail identification, whereas YOLOv9c-seg works well but may struggle with thick or complex tissue samples. The comparative analysis reveals that while YOLOv9c-seg performs adequately in standard scenarios, YOLOv11n-seg excels in complex imaging conditions, offering enhanced detection capabilities that are crucial for precise and reliable medical diagnostics.

## V. Discussion

The comparative analysis of YOLOv9c-seg and YOLOv11n-seg models for instance segmentation in medical imaging provides several important insights into their performance and practical applicability. The models were fine-tuned using transfer learning on the NuInsSeg dataset, which contains over 30,000 annotated nuclei, presenting a diverse and complex challenge for segmentation models. The experimental results clearly indicate that YOLOv11n-seg outperforms YOLOv9c-seg across multiple evaluation metrics. Notably, YOLOv11n-seg achieved higher values in precision (0.87), recall (0.84), and mAP50 (0.89), compared to YOLOv9c-seg. This suggests superior segmentation quality and a greater ability to accurately detect and delineate nuclei, particularly in complex or densely populated tissue regions. The reduced training and validation losses across all categories further affirm YOLOv11n-seg's improved generalization capabilities. The success of YOLOv11n-seg can be attributed to its architectural advancements, including enhanced attention mechanisms and deeper feature pyramids, which allow for more precise detection of small, overlapping, and irregularly shaped nuclei. Additionally, the significant reduction in parameters and computational complexity makes YOLOv11n-seg an attractive option for real-time clinical applications, achieving inference times of just 2.6 milliseconds per image. These findings support the primary objective of the study—to identify a more robust and efficient instance segmentation model for medical imaging. By demonstrating higher segmentation accuracy and faster inference with YOLOv11n-seg, the study confirms the advantages of integrating transfer learning and advanced architectural features for improving medical image analysis. These results highlight YOLOv11n-seg's strong potential for deployment in diagnostic tools and automated workflows within clinical and research settings.

## VI. Conclusion

This paper provided a detailed comparative analysis of fine-tuned one-stage object detection models for instance segmentation in medical imaging. Using the NuInsSeg dataset, which contains over 30,000 manually segmented nuclei across 665 image patches from various human and mouse organs, we presented the fine-tuned YOLOv9-seg and YOLOv11-seg architectures. The models were evaluated using key performance metrics, including precision, recall, mAP, and Intersection over Union (IoU). The experimental results demonstrate that the fine-tuned YOLOv11-seg outperforms YOLOv9-seg, with significant improvements in segmentation accuracy and mAP. YOLOv11-seg's advanced attention mechanisms and enhanced feature pyramids enable superior detection of small, densely packed, and irregularly shaped nuclei, making it a robust and efficient tool for complex medical imaging tasks.

Future studies may investigate the use of multi-modal imaging methods to provide more comprehensive contextual information, hence possibly improving segmentation accuracy. Furthermore, enhancing the computational efficiency of YOLOv11-seg for implementation in resource-limited contexts, such as mobile or embedded systems, would expand its practical use. Incorporating varied datasets and diseases into the assessment may enhance the models' resilience and scalability across numerous medical imaging contexts.

## Acknowledgment

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# Multitask Model with an Attention Mechanism for Sequentially Dependent Online User Behaviors to Enhance Audience Targeting

Marwa Hamdi El-Sherief, Mohamed Helmy Khafagy, Asmaa Hashem Sweidan
Faculty of Computers and Artificial Intelligence, Fayoum University, 63514 Egypt

***Abstract*—This paper proposes a multitask learning approach with an attention mechanism to predict audience behavior as sequential actions. The goal is to improve click-through and conversion rates by effectively targeting audience behavior. The proposed model introduces specific task sets designed to address the challenges specific to each prediction task. In particular, the first task, click prediction, suffers from data sparsity and a lack of prior knowledge, limiting its predictive power. To address this, a one-dimensional convolutional network (1D CNN) tower is used in the first task to learn local dependencies and temporal patterns of user activity. This design choice allows the model to better detect potential clicks, even without rich historical data. The task of conversion prediction is tackled by a fully connected convolution tower that selectively combines the corresponding features extracted from the first task using an Attention Mechanism, as well as the original shared embedding input data, enabling richer context for performing more accurate prediction. Experimental results show that the proposed multitask architecture significantly outperforms existing state-of-the-art models that do not consider tower architecture design to predict sequential online audience behavior.**

***Keywords*—Multitask learning; 1D convolution neural networks; attention mechanism; click through rate; conversion rate; audience behavioral targeting; audience behavior**

## I. Introduction

In Internet advertising, audience targeting delivers the right message to the right audience at the perfect time. It is a multifaceted process that depends on several factors and how they work together. Recently, researchers have become increasingly interested in using machine learning to improve audience targeting as the market's online advertising needs grow. Behavioral targeting (BT) [1], which considers the behavior of the online user, such as clicking links, visiting websites, submitting forms, sending messages, making purchases, etc., is one of the most efficient techniques for improving the target audience [2].

To reach the ultimate business goal of conversion, the user behavior in an advertising campaign takes a multistep path (impression $\rightarrow$ click $\rightarrow$ conversion). The terms" impression", "click", and "conversion" denote the frequency of an online advertisement's display, clicks, and conversions, which include purchases that include the number of clicks that result in an action. The ratio of clicks on an online advertisement to the times the online ad is presented is called the click-through rate, or "CTR" [3]. In contrast, the conversion rate (CVR) is the ratio of the number of people who convert to the number of clicks at first; efforts were focused on developing different models to predict the click-through rate (CTR) [4], which gauges the effectiveness of the campaign. It is difficult to capture complex interactions in advertising systems using traditional machine learning classification methods, such as linear regression, support vector classification (SVC), and decision trees, particularly when high-dimensional data are present. Furthermore, a variety of deep learning architectures are employed in advertising systems to capture interactions between high-order features, including long-short-term memory (LSTM) and convolution neural networks (CNN) [5] and [6].

However, calculating the exact return on investment (ROI) has become crucial for marketers dealing with Internet advertising. Due to the complexity of user behavior, both the CTR and CVR predictions are required. The issue of limited data and delayed feedback is the main barrier to the prediction of the conversion rate [7]. Furthermore, clicks and conversion behaviors are sequential and depend on a multi-step conversion path. Recently, multitask models have used click behavior to address the problem of sparse data in conversion behavior. Deep learning researchers are actively investigating multitask learning (MTL) [8]. Through shared information, this learning paradigm seeks to learn several related tasks to enhance performance and generalization collaboratively. MTL has been used effectively by several academics in a variety of areas recently, including recommendation systems [9], computer vision, natural language processing, and reinforcement learning.

Multitask learning has been frequently applied to improve end-to-end conversion rates in the audience's multistep conversion path. According to task relations, multitask learning is divided into parallel, cascaded, and auxiliary tasks in multitask deep recommendation systems [9]. In this instance, a sequential dependency between tasks is termed a cascading task connection, where the prior task influences the computation of the current task. Numerous cascaded task relation models have been presented in user behavior sequence prediction to address the problems of overfitting and data sparsity in training sparse conversion behavior data. The authors in [10] and [11] proposed multigate mixture of experts (MMoE) and progression-layered extraction (PLE), respectively, taking into account CTR and CVR as non-sequential tasks. To address the problem of the sequential nature of the user behavior input data, [12] proposed the mixture of sequential experts (MoSE) to represent sequential behavior using long-short-term memory (LSTM) in cutting-edge multigate mixture of expert multitask models. However, this technique lacks information sharing between the top-level towers in the model, which holds valuable information from the previous tasks to model click-through rate (CTR) and conversion rate (CVR) prediction by

two auxiliary tasks. Using an estimated conditional probability in the CVR task, the sequential dependence between user activities is taken into account in [13], [14], and [15].

To improve model performance, ESM2 [15] specifically masks conversion-related information during click prediction, therefore addressing the constraints of ESMM [13]. However, severe information loss might result from incorrect probability estimates. To overcome the difficulties of multitask learning with sequentially dependent tasks among multistep conversions, where prior tasks exchange valuable information with the subsequent task at the top of the tower [16], [17], and [18] proposed AITM, PIMM, and MNCM, respectively. Although many multitask learning models have been proposed for CTR and CVR prediction, most of them either overlook the sequential dependence across user behaviors or fail to share high-level task-specific information effectively among tasks. For example, models such as ESMM and MMoE don't explicitly model the action sequence of users or transfer informative signals from clicks to conversions using complicated mechanisms. Although recent models such as AITM, PIMM, and MNCM consider the sequential nature of user behavior, they still lack emphasis on the architectural design of task-specific towers. To the best of our knowledge, most of these models adopt simple feedforward networks as towers and overlook the potential benefits of using diverse tower structures. This is particularly crucial for the click prediction task, which suffers from a lack of prior knowledge and would greatly benefit from employing a more expressive architecture, such as a 1D convolutional network, to represent local temporal dependencies in user behavior. To address this gap, this paper proposes a novel multitask model that consists of a 1D CNN tower to improve the click prediction task and an attention-based mechanism to transfer beneficial information into the conversion prediction task. The proposed design addresses the challenges of data sparsity, sequential dependency, and task interaction of online user behavior prediction.

As a result, the following summarizes all the primary contributions in this paper:

1) Proposed a multitask model to improve audience behavioral targeting.
2) Shared embedding vector for all tasks.
3) Using 1D CNN improves the first task tower.
4) Use the attention mechanism to identify useful information from the information provided.
5) Processing of the Ali-CCP dataset.
6) Pre-processing of the Taobao dataset and feature engineering to be relevant to our work.
7) The data loader to access processed data that can be parallelized and shuffled.

Therefore, the remainder of this paper is structured as follows: Section II reviews the related work in multitask learning and user behavior modeling. Section III presents the proposed architecture in detail. Section IV explains the datasets, the preprocessing pipeline, and the experimental setup. Section V discusses the experimental results and performance evaluation. Finally, Section VI concludes the paper and suggests directions for future research.

## II. Related Work

This section reviews recent studies on online audience behavior targeting using machine learning [19]. Previous research has shown that machine learning greatly improves the online audience-targeting process. Recent research uses multitask models to improve multistep user conversion path (click $\rightarrow$ conversion) returns [9]. According to task relation, models are classified into non-sequential tasks and sequential dependence tasks, as shown in Table I.

### A. Non_Sequential Tasks

In studies [10], [11], and [12], tasks are non-sequential and are modeled separately. The multi-gate mixture of experts (MMoE) [10] uses network gates to bring together experts for various tasks, improving the model's capacity to capture complex task-specific patterns. The model AUCs are 0.6420 for purchases and 0.6047 for clicks.

The authors of study [11] presented a progressive layered extraction (PLE) model that clearly distinguishes between task-specific and task-shared experts to address the seesaw problem, which occurs when improving one task's performance may affect the performance of another task. The AUC models for click and conversion are, respectively, 0.6039 and 0.6417.

The authors of study [12] introduced MoSE. This model models user activity streams using long-short-term memory (LSTM) and offers a comprehensive sequential solution with a gated mixture of experts. After extensive testing with real-world G Suite user data, MoSE outperforms the production model with an AUC score of +4.8%.

In studies [10], [11], and [12], the mixture of experts shares expert modules across all tasks at the bottom of the multi-task model. However, the inability to exchange information between tasks in top towers, which contain richer and more useful information, may limit their ability to improve each other.

### B. Sequential Dependence Tasks

Models are created to handle dependency-based actions, which means that when the first step is completed, the subsequent step could occur due to a sequential dependency.

The authors proposed the Entire Space Multitask Model (ESMM) in [13], which takes into account the sequential dependence between tasks and the probability of transfers for various activities to calculate the click and conversion rate (CTCVR) by calculating the product of (CVR) and (CTR). The model gets AUCs of 0.6022 and 0.6291 for click and conversion, respectively.

The authors of study [15] introduced ESM$^2$ to deliberately hide conversion-related information during click prediction to overcome the shortcomings of ESMM [13]. This method enhances model performance by using conditional probability rules based on user behavior graphs to convey fundamental information. However, it ignores richer representations in vector space, which results in a severe loss of information if any probability prediction is off.

In study [16], the authors proposed an AITM (Adaptive Information Transfer Multitask) to simulate multistep conversions and sequential reliance of the audience. To improve the performance of sequentially dependent multitask learning, the suggested adaptive information transmission (AIT) module combines the behavioral expectation calculator in the loss function to acquire knowledge of what and how much information to transmit for different conversion phases. With the Ali CCP dataset, AITM achieves AUCs of 0.6043 and 0.6525 for click and purchase, respectively. The authors of study [18] proposed the multilevel network cascades model (MNCM) with two adaptive information transfer modules, the task-level information transfer module (TITM) and the expert-level information transfer module (EITM), to address the information lacking in the first task. They achieve AUCs of 72.15, 87.16, 71.06, and 86.44 on click and buy, respectively, using the AliExpress-NL and AliExpress-US datasets. The authors used the prior information merged model (PIMM) to learn sequentially dependent tasks in [17]. The PIMM combines explicit premise information (i.e., probability of previous positive reinforcement) with latent representations (specialized knowledge) to strictly describe the logical dependency among tasks as learning several sequential dependence tasks under a curriculum-structured guidance. Using a soft sampling method, PIM randomly chooses the real label information to transfer to the downstream task during training, adhering to a curriculum paradigm that ranges from basic to advanced. They obtain AUCs of 0.6075 and 0.6561 for click and buy, respectively, using the Ali CCP dataset.

Most of the reviewed literature addressed the problem of targeting online audience behavior, and current models often fail to account for the dynamic nature of user behavior, which changes over time due to different factors, including evolving interests, outside influences, and seasonal trends. To bridge these gaps, the proposed approach in this paper uses a CNN tower for the click task to handle the absence of prior information in the first task. Furthermore, the attention method is utilized to convey pertinent information from the click task to manage sparse data in the conversion task.

## III. The Proposed Model

In this paper, the methodology used to apply a multitask model with an attention mechanism [20] to anticipate the behavior of an online audience, which is intended to predict user clicks and conversion behaviors while accounting for the sequential dependency between these events; this means that the conversion event depends on the click event that occurred previously. Furthermore, as seen in Fig. 3, the shared embedding layer, the click tower, the conversion tower, the attention mechanism, and the click information extraction are the components of the proposed approach.

The approach consists of the following main phases:

### A. Preprocessing of Data

The preparation of the data phase is crucial to the proposed model. To deal with various types of characteristics in the input data and to guarantee that the input data is consistent with the nature of sequentially dependent events. The preparation step consists of the following individual stages:

*1) Data cleaning and transformation:* The data cleaning and transformation process involved several key steps in preparing the dataset for modeling. First, missing values were identified and eliminated, as they did not significantly affect the performance of large datasets. Then, low-frequency characteristics, those with fewer than ten occurrences, were removed to enhance the conciseness and relevance of the input data. The numerical features were normalized to the same scale as the variables. Categorical characteristics were encoded to convert them to a numeric form so that they could be analyzed. In addition, timestamp fields were converted into a uniform date-time format to support temporal analysis. Finally, the data were ordered by user and date time to meet the sequential input data requirements.

*2) Feature engineering:* Generate additional features based on past user behavior.

*3) Data splitting:* divide the dataset into testing, validation, and training sets based on the number of days.

### B. Data Loader

In the proposed model, the data loader plays a critical role in optimal data batching, shuffling, and loading. It begins by partitioning data and pulling associated feature names, and targets with sequential dependencies such as clicks and conversions. As an indication of process optimization, the data are batched according to a specified batch size. In addition, the data are randomized during training to improve the model's generalization capacity. Importantly, the data are dynamically loaded, which is extremely beneficial when dealing with a large dataset.

### C. Shared Embedding Layer

During this stage, the embedding methods convert all input characteristics into low-dimensional dense vectors of a given size [21]. To create a common embedding module, all embedding vectors must be concatenated. By sharing the embedding layer between all tasks, the model can benefit from rich positive samples of previous tasks, which promotes information sharing and reduces the impact of the class imbalance conversion task. Sharing the embedding layer also contributes to reducing the total number of model parameters.

### D. Click Task

This stage consists of two phases: click tower and click probability. Since the click tower, which represents the first task, has a significant impact on all subsequent tasks, as it suffers from a lack of useful information, since there are no previous tasks in this stage, this paper presents a new construction for the click tower, which addresses the representation of features using one-dimensional convolutional neural networks [22] as the tower. 1D Convolution Neural Networks are a unique kind of CNN in which the kernel analyzes one-dimensional input, such as sequential and temporal series. In CNN, the output size No is estimated as in Equation (1), the kernel size K refers to the size of the sliding kernel or the kernel filter, The number of kernels that slide before producing the output and the product points is known as the stride length S, and the size of the 0-Th frame that surrounds the input feature map $N_n$ is known as padding P [23]. The proposed

TABLE I. SUMMARY OF SURVEYED STATE-OF-THE-ART MULTITASK MODELS FOR ONLINE USER BEHAVIOR PREDICTION

| Study | Model | Dataset(s) | Model Type | Tasks | Evaluation Metric(s) | Year |
|---|---|---|---|---|---|---|
| [13] | **ESMM** | Taobao's recommender system logs | DNN | CVR, CTR, CTCVR, SPP | Multi-AUC | 2018 |
| [10] | **MMOE** | Synthetic dataset, UCI Census | Neural network (8 hidden units) | CTR, CVR | AUC | 2018 |
| [11] | **PLE** | Census-income, synthetic data, Ali CCP | LSTM | CTR, CVR | AUC | 2020 |
| [12] | **MoSE** | Generated synthetic dataset | MLP | Task1, Task2 | PR-AUC | 2020 |
| [16] | **AITM** | Ali CCP | MLP | CTR, Buy, Approval, Activation | AUC | 2021 |
| [18] | **MNCM** | AliExpress | MLP | CTR, CVR | AUC | 2022 |
| [17] | **PIMM** | Ali CCP | MLP | CTR, CVR | AUC | 2023 |

model used multiple layers of a 1D convolution network to process the shared and embedded input characteristics, varying the stride and padding for every kernel size as specified by Eq. (1). Furthermore, weight normalization is handled by ReLU activation functions, and regularization is accomplished via the dropout approach. To pass through fully connected layers, the output of the 1D convolution layers is flattened, as shown in Fig. 1. Furthermore, the second phase is the click probability, which uses a sigmoid activation function to process the output data from the click tower after passing through a linear neural network to determine the output probability.

$$\mathbf{N_o} = \left(\frac{N_n - \mathrm{K} + 2 \times \mathrm{P}}{\mathrm{S}}\right) + 1 \tag{1}$$

### E. Information Extraction

For the conversion task and other behaviors that follow, the information extraction phase is essential to improve the prediction process; learning is transferred between tasks through the attention mechanism, as shown in Fig. 2; the attention mechanism enhances the model's ability to recognize pertinent parameters required for the conversion task [24], and [25], which frequently involves sparse input. The attention mechanism that combines the information from the click information tower and the conversion tower, as shown in Fig. 3, where the feed-forward networks $Q(a)$, $K(a)$, and $V(a)$ represent the input vector to a single new vector representation, dot attention uses a dot product to determine how comparable queries $Q(a)$ and Key $K(a)$ are and scaled by dimension $\sqrt{d}$ in Eq. (2), and Eq. (3) uses a softmax function to determine attention weights $w_a$. Eq. (4) computes $z_t$, the weighted sum of the value vectors $V(a)$ using these attention weights $w_a$.

$$\mathbf{w_a} = \frac{Q(a) \cdot k(a)}{\sqrt{d}} \tag{2}$$

$$\mathbf{w_a} = \mathrm{softmax}(w_a) = \frac{\exp(w_a)}{\sum_a \exp(w_a)} \tag{3}$$

$$\mathbf{z_t} = \sum_a w_a \cdot V(a) \tag{4}$$

### F. Conversion Task

This phase handles subsequent tasks using valuable knowledge obtained from the previous task, specifically from the click tower. It begins with the conversion tower, where a fully connected neural network is used to process input coming from the shared input embedding vector. Then, an information vector is generated using a feedforward neural network that models the output of the click tower. To enhance the learning process, an attention mechanism is applied to the output of the conversion tower, which is concatenated with the information vector of the previous task. In this step, the model can successfully utilize the knowledge acquired in the earlier stages. Lastly, the probability of conversion is found by feeding the attention output into a linear neural network, then applying the sigmoid activation function to get the final prediction.

### G. Loss Calculation

The final loss function $L_f$ in our suggested model is determined by calculating the loss of cross entropy $L_c$ and the behavioral expectation calibrator $L_{bc}$ combined with a constant weighting parameter $\alpha$ that regulates the behavioral force expectation calibrator as indicated in Eq. (7). The loss is determined using the binary cross-entropy loss ($L_c$) indicated in Eq. (5), where $y$ is the label, $\hat{y}$ is the target value, T is the task, and N is the number of samples. In addition, a calibration of behavioral expectations ($L_{bc}$) indicated in Eq. (6) is added to ensure that the model result meets the actual production constraints, where the click task is expected to have a higher probability than conversion for the same user because click and conversion are sequentially dependent behaviors.

$$\mathbf{L_c}(y, \hat{y}) = -\frac{1}{N} \sum_T \sum_N \left(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})\right) \tag{5}$$

$$\mathbf{L_{bc}} = \frac{1}{N} \sum_T \sum_N \max(\hat{y}_{cl} - \hat{y}_{co}, 0) \tag{6}$$

$$\mathbf{L_f} = L_c + \alpha L_{bc} \tag{7}$$

### H. Evaluation

The proposed approach adopts the AUC, or Area Under the ROC Curve, which is a commonly used evaluation metric in

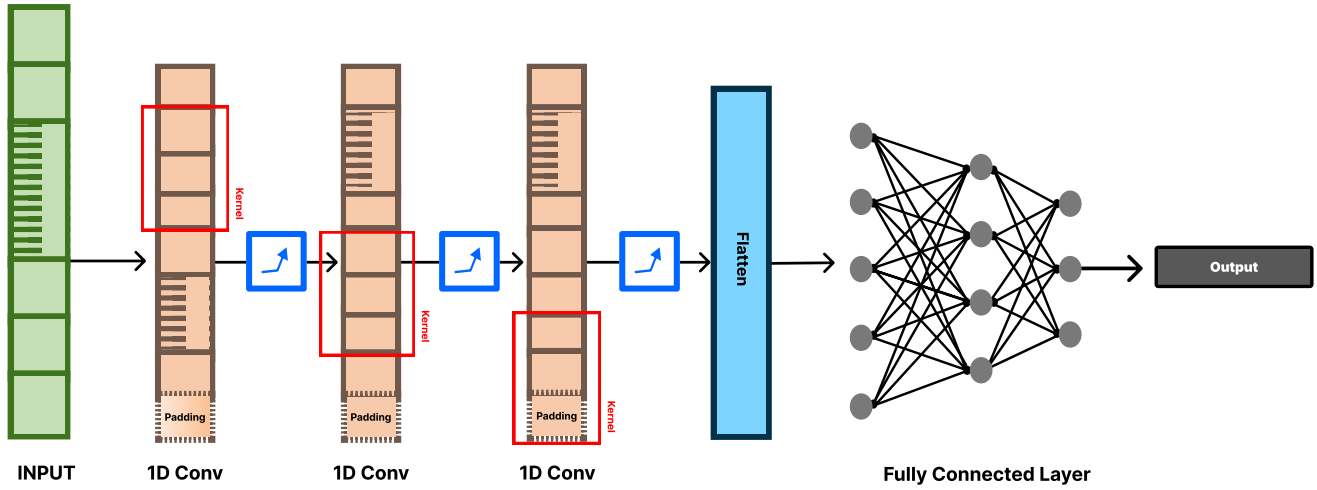


Fig. 1. 1D Convolution network.

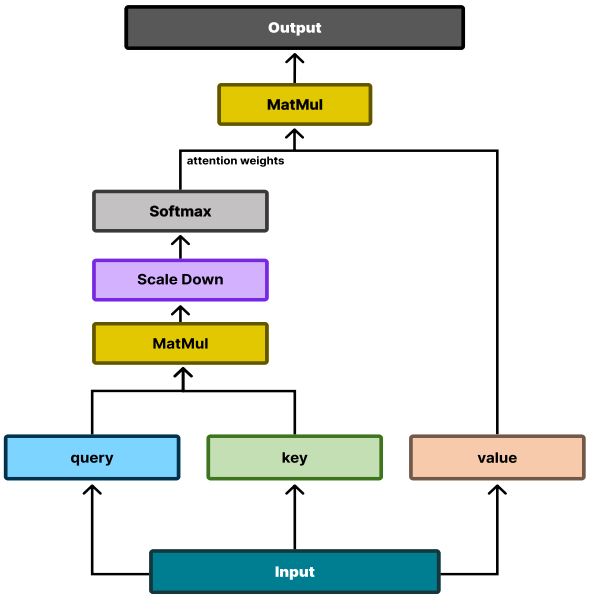


Fig. 2. Attention mechanism.

recommendation systems. Shows the probability that an item that has been clicked will rank higher than an item that has not been clicked.

## IV. Results and Discussion

### A. Datasets and Evaluation Metrics

Two public datasets were utilized in this study: Ali-CCP [13] and Taobao User Behavior for recommendation [26].

*1) Ali-CCP Dataset [13]:* This dataset is an actual traffic log from Taobao's recommendation system. The end-to-end user conversion process consists of several consecutive phases, starting from impression, moving to click, and eventually conversion (i.e., impression → click → conversion). Each observed impression is associated with a feature vector, denoted by x, representing both the user and item information. The label format is (x, y → z), where y and z are binary variables indicating whether a click (1) or no click (0), and a conversion (1) or no conversion (0), occurred, respectively. Here, as sequential tasks, the conversion can only happen if a click has occurred beforehand. The dataset exhibits significant data sparsity, as evidenced by the calculated click-through rate (CTR) and conversion rate (CVR), which are 3.89% and 0.54%, respectively, as illustrated in Fig. 4.

In the data preprocessing phase, the dataset is divided into subsets for training, validation, and testing. 50% of the data is allocated for training, 10% for validation, and the remaining 40% for testing. Low-frequency features—those with fewer than ten occurrences—are excluded, and categorical features are appropriately coded to prepare the data for input into the model. Analysis of the dataset shows that the most influential factor is the product categories the user has previously clicked on. This result demonstrates the importance of modeling user behavior history, as it has a significant impact on the prediction goal.

*2) User behavior data from Taobao for recommendation dataset [26]:* contains around 100 million user activities and serves as an essential resource for research and analysis, particularly in user behavior modeling. The dataset includes user behaviors gathered from one million randomly chosen Taobao users and records a wide range of online activities over nine days. As illustrated in Fig. 5, 846.9k users browse the items, while 6.20% add them to carts, 3.13% favorite them, and 2.27% proceed to purchase.

Regarding the preprocessing of the user behavior data from the Taobao recommendation dataset [26], the proposed approach narrowed the study to a nine-day observation period to check the fitness of the data and accelerate the processing time. It also determined the sequential dependency of the "buy"

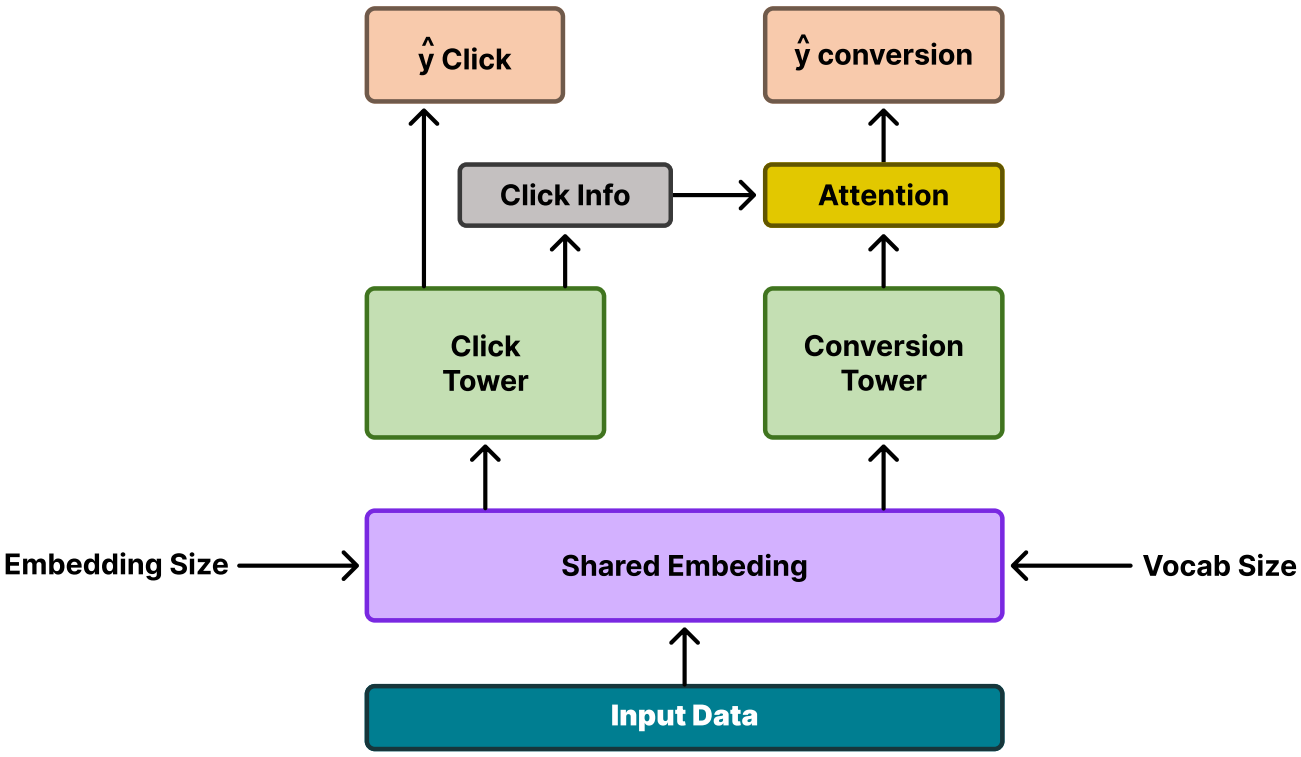


Fig. 3. Proposed model: Multitask model for sequential online user behaviors (click and conversion) with different tower architectures

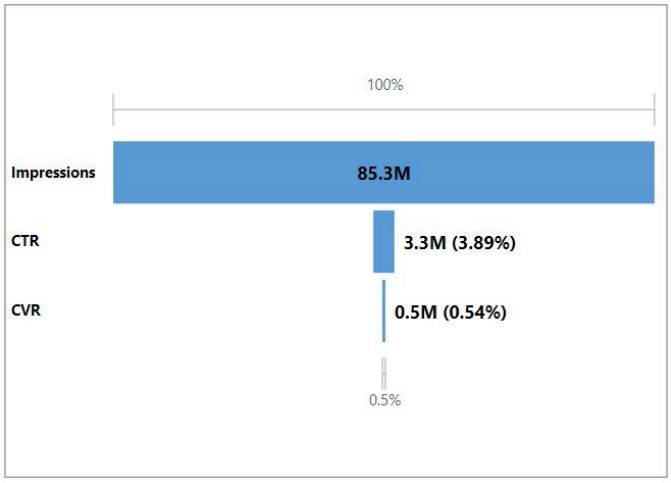


Fig. 4. Statistics of Ali_CCP dataset.

and "add-to-cart" activities, encoding the category feature "behavior" to distinguish between different activities. Data cleaning followed, excluding non-conforming products from the desired browsing-to-purchase pattern. The data preparation to supply deep learning models was ordered chronologically by user and date. This form allows the model to learn time dependencies and improve the model's ability to identify patterns and make consistent predictions. Furthermore, the presentation of the events in time-ordered sequence is consistent with the natural progression of user interactions and therefore improves the model's ability to learn meaningful information. To feature engineer the user behavior data of the Taobao recommendation dataset [26], additional historical data was incorporated, including the user's previous activities and the product categories on which the user previously clicked. This enhancement provides a contextual understanding of user behavior with more enrichment so that analysis can be deeper and more effective.

## V. Experimental Analysis

This article's studies were carried out using a PC equipped with a 16 GB GPU, 32 GB of RAM, and a 2.7 GHz Intel Core i7 CPU. The PyTorch Python libraries were used to develop our suggested strategy. Data are preprocessed using Apache Spark in Python (PySpark) to handle massive volumes of data in a distributed processing environment, especially to generate new historical characteristics that increase the size of the data. Two distinct open datasets were used to evaluate the suggested hypothesis. 4.10 GB of compressed train data and 4.68 GB of compressed test data make up the Ali CCP dataset. In comparison, the Taobao user behavior data used for the recommendation weighs 5 GB after compression.

The dictionary of vocabulary size in the embedding layer is set to the unique value of each input feature, and the embedding size is set to five. The proposed approach was experimented with different kernel sizes for the 1D Convolution

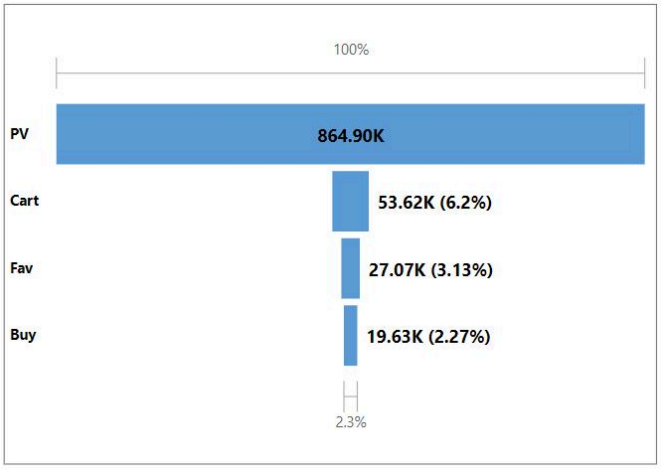


Fig. 5. Statistics of user behavior data from Taobao for recommendation dataset.

TABLE II. EVALUATION METRICS FOR CLICKS ON ALI-CCP PUBLIC DATASET FOR DIFFERENT MODELS

| Model | AUC | Accuracy | Recall | Specificity |
|---|---|---|---|---|
| AITM Model | 0.614 | 0.6 | 0.61 | 0.61 |
| Proposed Model | 0.661 | 0.64 | 0.66 | 0.66 |

tower to obtain the optimal AUC and adjusted the padding by Eq. (1). The input dimensions for the proposed approach are 128, 64, and 32 in the linear tower. The proposed approach was trained with a batch size of 1,000 samples over five epochs.

### A. Comparative Evaluation of State-of-the-Art Models

This subsection compares the performance of the suggested model with the most advanced model, AITM. The performance of the proposed model was evaluated against the AITM model using two public datasets, Ali-CCP and Taobao, using evaluation metrics such as AUC, accuracy, recall, and specificity. ROC curves are presented to visually represent the performance of the models. Fig. 6 shows the ROC curve for the AITM model in the public dataset of the Taobao recommendation. Similarly, the ROC curves for the proposed model are shown in Fig. 7 for the Ali CCP public dataset and Fig. 8 for the Taobao recommendation public dataset. These curves highlight the comparative ability of each model to distinguish between classes.

*1) Model performance on Ali CCP dataset:* In terms of model performance on the Ali CCP dataset, the click task results show that the proposed model achieved an AUC of 0.661, which was better than the AITM model with an AUC of 0.614, as presented in Table II and Fig. 9. For the conversion task, the AUC of the proposed model increased further to 0.694 compared to 0.6320 for the AITM model, demonstrating the improved performance of the proposed model, as presented in Table III and Fig. 10.

*2) Model performance on the taobao dataset:* Concerning the performance of the model in the Taobao dataset, the results of the click task show that the proposed model obtained an AUC of 0.682, compared to that of the AITM model, which

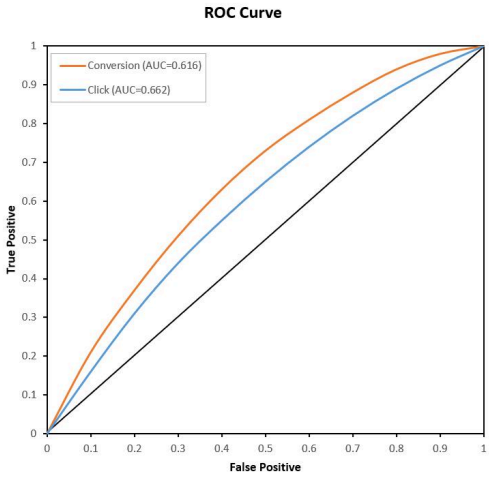


Fig. 6. ROC Curve for AITM model on the Taobao recommendation public dataset.

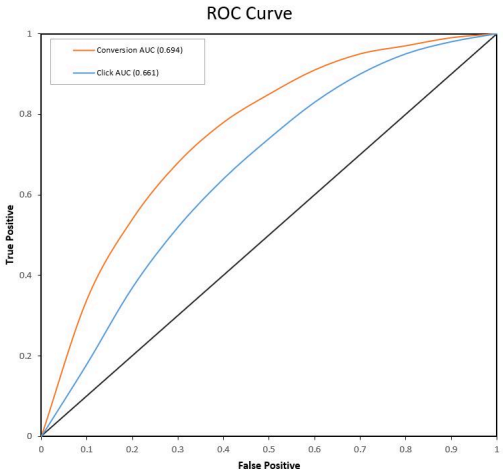


Fig. 7. ROC Curve for the proposed model on Ali-CCP public dataset.

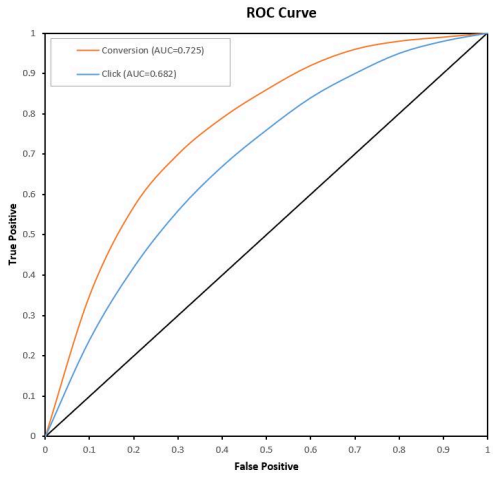


Fig. 8. ROC Curve for the proposed model on the Taobao recommendation public dataset.

TABLE III. EVALUATION METRICS FOR CONVERSION ON ALI-CCP PUBLIC DATASET FOR DIFFERENT MODELS

| Model | AUC | Accuracy | Recall | Specificity |
|---|---|---|---|---|
| AITM Model | 0.632 | 0.62 | 0.63 | 0.63 |
| Proposed Model | 0.694 | 0.68 | 0.69 | 0.69 |

TABLE IV. EVALUATION METRICS FOR CLICKS ON THE TAOBAO RECOMMENDATION PUBLIC DATASET FOR DIFFERENT MODELS

| Model | AUC | Accuracy | Recall | Specificity |
|---|---|---|---|---|
| AITM Model | 0.616 | 0.6 | 0.62 | 0.62 |
| Proposed Model | 0.682 | 0.65 | 0.68 | 0.68 |

TABLE V. EVALUATION METRICS FOR CONVERSION ON THE TAOBAO RECOMMENDATION PUBLIC DATASET FOR DIFFERENT MODELS

| Model | AUC | Accuracy | Recall | Specificity |
|---|---|---|---|---|
| AITM Model | 0.662 | 0.63 | 0.66 | 0.66 |
| Proposed Model | 0.725 | 0.7 | 0.73 | 0.73 |

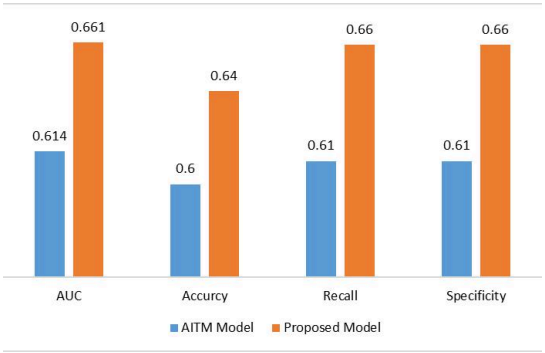


Fig. 9. Evaluation metrics for click on Ali-CCP public dataset for different models.

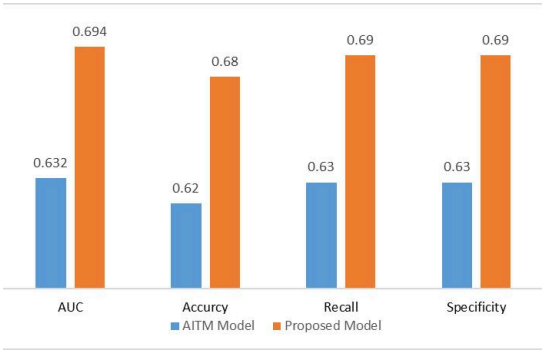


Fig. 10. Evaluation metrics for conversion on Ali-CCP public dataset for different models.

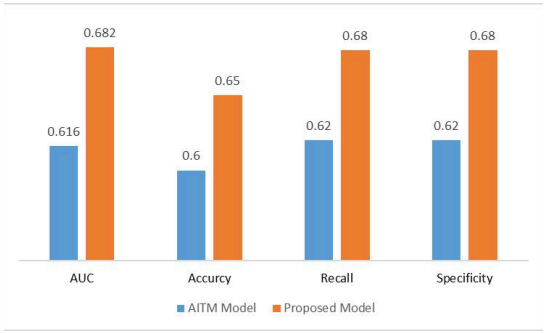


Fig. 11. Evaluation metrics for clicks on the Taobao recommendation public dataset for different models.

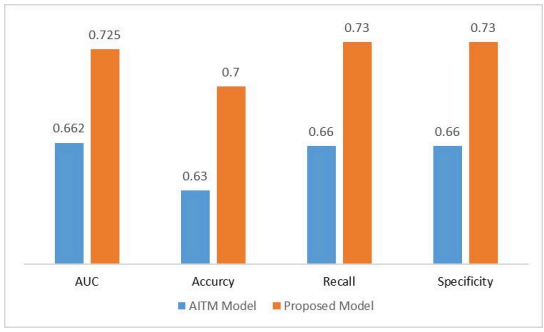


Fig. 12. Evaluation metrics for conversion on the Taobao recommendation public dataset for different models.

obtained an AUC of 0.616, as shown in Table IV and Fig. 11. As illustrated in Table V and Fig. 12, the differences were further noticeable for the conversion task, where the suggested model received an AUC of 0.725 compared to 0.662 for the AITM model.

Furthermore, the results suggest that the Taobao dataset may have slightly different structural properties than the Ali CCP dataset, resulting in marginally better model performance. This insight into the impact of the characteristics of the data set on model performance is valuable for future research.

## VI. CONCLUSION

To improve audience targeting in online advertising, this research proposes a novel multitask model to evaluate sequential user behavior online, which could help with audience targeting. The method presents a unique multitasking model with several tower architectures specific to the task. For the click task (the first task), the proposed approach uses 1D convolutional neural networks without prior knowledge to improve audience targeting by focusing on those most likely to click. In the conversion task (the subsequent task), which utilizes information from the first task, a fully connected tower is used along with an attention mechanism. The suggested method outperforms another state-of-the-art multitask model (AITM) [16] in simulating user behavior with sequential online dependencies. Future studies may need to investigate more intricate tower architectures to overcome the restrictions above.

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# Secure Optimization of RPL Routing in IoT Networks: Analysis of Metaheuristic Algorithms in the Face of Attacks

Mansour Lmkaiti[1], Maryem Lachgar[2], Ibtissam Larhlimi[3], Houda Moudni[4], Hicham Mouncif[5]
LIMATI Laboratory-Polydisciplinary Faculty, University Sultan Moulay Slimane, Morocco[1,2,3,5]
TIAD Laboratory-Faculty of Sciences and Technology, University Sultan Moulay Slimane, Morocco[4]

***Abstract*—The security and efficiency of Internet of Things (IoT) networks depend on optimizing the routing protocol for low-power, lossy networks (LPNs) to manage various challenges, including expected number of transmissions (ETX), latency and energy consumption. This study proposes an advanced metaheuristic optimization framework integrating several algorithms, including Particle Swarm Optimization (PSO), Mixed Integer Linear Programming (MILP), Adaptive Random Search with two-step Adjustment (ARS2A) and Simulated Annealing (SA), to improve the performance of RPL-based IoT networks under attack scenarios. Our methodology focuses on secure routing by integrating dynamic anomaly detection and adaptive optimization mechanisms to mitigate network threats such as Blackhole, Sinkhole, and Wormhole attacks. Simulations were carried out on large-scale IoT networks with 100 and 150 nodes to evaluate the performance of the proposed algorithms. Experimental results indicate that ARS2A and MILP offer the best compromise between security and performance, achieving minimal ETX (1.28), reduced latency (0.12 ms) and optimized energy consumption (0.85 J) in dense networks. Furthermore, simulated annealing demonstrates high adaptability to mitigate routing attacks while guaranteeing stable energy efficiency. The comparative analysis highlights the strengths and weaknesses of each algorithm, underscoring the need for hybrid optimization strategies that balance computational cost and real-time adaptability. This work establishes a secure and scalable optimization framework for IoT networks, contributing to the development of intelligent, resilient and energy-efficient routing solutions.**

***Keywords*—IoT Security; PSO; MILP; ARS2A; simulated annealing; RPL protocol; metaheuristic techniques; routing efficiency; ETX; latency; energy consumption; attack mitigation; blackhole; wormhole; grayhole; cyberattack**

## I. Introduction

Mission-critical applications in fields including smart cities,industrial surveillance-health [1], and critical infrastructure management have emerged as a result of the Internet of Things (IoT) explosive growth. These networks [2], which are composed of linked sensor nodes,need to optimize energy use while guaranteeing safe and effective data transfer. However, their decentralized architecture, coupled with limited hardware resources, exposes them to major challenges, particularly in terms of reliability, energy efficiency and security against cyber-attacks. The Routing Protocol for Low-Power and Lossy [3] Networks is one of the numerous vulnerabilities in these networks are of particular concern. Numerous attacks take advantage of RPL flaws to interfere with routing and jeopardize data transfer. The most destructive of these are the Blackhole [4], Sinkhole, Wormhole and Selective Forwarding attacks, which reroute, delay, or eliminate packets moving throughout the network. These threats [5] have a direct impact on network performance, increasing the number of retransmissions required (ETX), latency and energy consumption. These degradations have the potential to cause significant system failures in critical applications,like medical and environmental networks, endangering the availability and integrity of services.

The development of sophisticated attack detection [6] and mitigation techniques that can preserve the best possible balance between security energy efficiency [7], and quality of service(QoS) is essential in light of these expanding threats. Traditional cryptography-based solutions and authentication often prove unsuitable for IoT networks [8] due to the energy and computing constraints of sensors. Therefore,a more dynamic and intelligent strategy that incorporates cutting-edge optimization techniques [9] is needed to improve routing resilience while lowering energy expenses.

In light of this,our work suggests a novel strategy that combines behavioral analysis methods with metaheuristic optimization algorithms [9], in order to secure IoT networks against attacks targeting the RPL protocol [10]. Optimizing packet routing is the goal by taking into account three fundamental metrics:

- Expected Transmission Count (ETX): Indicator of link quality, measuring the Average number of transmissions required to route a packet. A high ETX value reflects increased routing instability, often caused by attacks or interference.
- Latency: Total time required to transmit a packet from the source node to the destination node. Excessive latency is often a symptom of the presence of attacks such as Wormhole, Flooding or Selective Forwarding.
- Consumed Energy [11]: Total amount of energy consumed by nodes during transmissions. An abnormal increase in this metric is generally a sign of attack, resulting from artificially generated traffic or packet hijacking.

In order to optimize safety and network resilience, we use four sophisticated optimization algorithms [12]:

- Simulated Annealing: Enhances routing robustness by facilitating effective solution space exploration while avoiding local minima.

- Particle Swarm Optimization: Simultaneously minimizes latency and energy consumption, based on how particles behave collectively.
- Mixed Integer Linear Programming: Ensures safe and reliable routing by offering the best solution under tight restrictions.
- ARS2A (Adaptive Random Search with Two-Step Adjustment): Adaptive routing optimization is a new high-performance algorithm that allows for dynamic enhancements in IoT network performance.

By integrating these various methods, we provide a strong attack detection [13] and mitigation strategy that can dynamically adjust to threats while preserving optimal energy efficiency. By increasing network stability, our solution dramatically lessens the effect of attacks on routing, as demonstrated by our tests conducted on network with 100 and 150 nodes, reducing latency and optimizing energy consumption. These results confirm the importance of a hybrid approach combining security and metaheuristic optimization to ensure reliable, energy-efficient and resilient routing in modern IoT environments [14]. The remainder of this paper is structured as follows: Section II provides an overview of related work in the field of secure RPL-based IoT routing. Section III presents the problem formulation, detailing the key challenges and security threats addressed in this study. Section IV describes the metaheuristic algorithms employed, including PSO, MILP, ARS2A, and Simulated Annealing, and their application to secure and energy-efficient routing optimization. Section V discusses the experimental setup and performance evaluation, comparing the effectiveness of different algorithms under various network configurations and security attack scenarios. Finally, Section VI concludes the paper by summarizing key findings and suggesting future research directions to enhance the robustness and scalability of secure RPL-based IoT networks.This research aims to answer the following question: How can metaheuristic algorithms be effectively utilized to optimize secure routing in RPL-based IoT networks while minimizing ETX, latency, and energy consumption under attack conditions?

## II. Related Work

Due to the increase in cyber threats [5], a lot of research has been done recently on the security of Internet of Things networks [14], especially in relation to routing Protocol for Low-Power and lossy Networks.To address vulnerabilities in RPL-based IoT systems [15], a number of research projects have investigated the combination of machine learning [16], [17], metaheuristics algorithms [18], and security-enhancing techniques [19]. The rapid expansion of IoT networks has introduced significant challenges in energy efficiency, security, and routing optimization. Various studies have explored solutions leveraging metaheuristic algorithms and security mechanisms to mitigate threats and optimize network performance. The application of metaheuristic algorithms to improve routing effectiveness and reduce energy consumption in IoT networks has been the subject of numerous studies. Choudhary et al. [12] carried out a thorough investigation to enhance routing security and efficiency in IoT environments by merging metaheuristic approaches with convolutional Neural Networks. Their findings highlight the potential of hybrid AI-metaheuristic models in optimizing path selection while mitigating security threats. Similarly, Rahmani et al. [18] investigated the use of metaheuristic algorithms for task offloading optimization in cloud, fog, and edge computing settings. Their strategy showed increased resource allocation effectiveness and delay reduction, making it a viable technique for extensive IoT deployments.

Security is a major issue in IoT networks, especially in low-power and lossy networks (LLNs) that rely on RPL routing. Omar et al. [10] introduced UOS_IOTSH_2024, a dataset specifically designed for analyzing sinkhole attacks in RPL-based IoT networks, providing a benchmark for evaluating intrusion detection systems. Reshi et al. [20] suggested a unique defense against blackhole attacks, showing how preventative security measures can lower packet loss and improve network robustness.

Further, Yalli et al. [14] carried out a thorough analysis of IoT authentication methods,emphasizing biometric-based access restrictions,AI-driven authentication models, and lightweight cryptographic protocols as crucial ways to increase IoT security. Additionally, Kadri et al. [13] offered a thorough analysis of Dos and DDOS attack detection in Internet of Things environments, categorizing current solutions according to mitigation techniques and validation methods. Their results demonstrate that hybrid models combining anomaly detection and heuristic-based prevention offer significant benefits in securing IoT networks against large-scale attacks.

In the context of routing security, Moudni et al. [4] investigated the detection of blackhole attacks in Mobile Ad Hoc Networks (MANTEs) using machine learning. Their findings showed how adaptive learning algorithms and tailored datasets may be used to detect and stop harmful activities. Similarly, Karima et al. [19] demonstrated the promise of AI-driven adptive security frameworks by proposing a method based on SDN and AI to dynamically improve IoT security policies.

Optimizing IoT networks while maintaining security in IoT routing, the relationship between security measures and metaheuristics has drawn more attention. Yugha et al. [21] provided an extensive survey on security protocols for next-generation IoT networks, emphasizing the importance of lightweight cryptographic methods that do not compromise energy efficiency. P. M. R. et al. [11] highlighted the trade-offs between network performance, security, and energy restrictions in their analysis of energy-aware routing strategies. These studies collectively suggest that a hybrid approach, integrating metaheuristic algorithms for optimization and advanced security mechanisms, could significantly enhance the resilience and efficiency of IoT networks. Future research should focus on scalable, AI-driven security models and adaptive optimization techniques to ensure sustainable and secure IoT deployments. Although various studies have explored the use of metaheuristics and AI-based approaches for enhancing RPL-IoT routing security and efficiency, few have provided a unified solution that simultaneously addresses resilience against multiple attack types and optimization of key metrics such as ETX, latency, and energy consumption. To bridge this gap, our study proposes a novel hybrid metaheuristic framework integrating ARS2A, MILP, PSO, and Simulated Annealing, which collectively aim to enhance security and performance under realistic attack scenarios.

## III. Problem Statement

In the section we formulate the RPL-based IoT networks optimization problem considering the following metrics:$ETX$, the latency ($LT$) and the energy consumption ($EC$). The objective function integrating these criteria is defined as follows [15],

$$Minimize\ F = \ w_1.ETX + \ w_2.LT + \ w_3.EC \quad (1)$$

Where $w_1$, $w_2$ and $w_3$ are weights assigned to $ETX$, $LT$ and $EC$ respectively.

### A. Define the Metrics

$ETX$ measures the number of expected transmissions, including retransmissions, required to successfully deliver a packet over a link.

$$ETX_{ij} = \frac{1}{P_{ij}.P_{ji}}$$

Where $P_{ij}$ is the probability of successful packet transmission from node $i$ to node $j$, and $P_{ji}$ is the probability of successful acknowledgment.
$LT$ represents the time required for a packet to travel from the source to the destination.

$$LT_{ij} = \ d_{ij} + \sum_k ProcessingTime_k$$

Where $d_{ij}$ is the propagation delay between nodes $i$ and $j$, and the sum represents the processing delays at intermediate nodes.
$EC$ is the of energy consumed to transmit a packet from the source to the destination.

$$EC_{ij} = \ TE_{ij} + \sum_k ProcessingEnergy_k$$

Where $TE_{ij}$ is the energy consumed for transmission between nodes $i$ and $j$, and the sum represents the energy consumed at intermediate nodes for processing.

### B. Formulate the Constraints

The connectivity constraint ensures that the selected path maintains network connectivity [15].

$$\sum_{j \in N} x_{ij} = 1, \ \ \forall\ i \ \in \ N$$

Where $xij$ is a binary variable indicating whether the link between nodes $i$ and $j$ is part of the path (1) or not (0). The Loop-Free constraint ensures that routing path does not exceed the available energy at any node.

$$\sum_{j \in N} x_{ij} = 1, \ \ \forall\ i \ \in \ N$$

The energy constraint ensures that the energy consumption does not exceed the available energy at any node.

$$EC_{ij} \ \leq \ E_i, \ \ \forall\ i \ \in \ N$$

Where $E_i$ is the available energy at node $i$.

### C. Optimization Problem Formulation

$$Minimize\ F = \sum_{i,j \in E} (w_1.ETX_{ij} + w_2.LT_{ij} + w_3.EC_{ij}).x_{ij}$$

Subject to:

$$\sum_{j \in N} x_{ij} = 1, \ \ \forall\ i \ \in \ N$$

$$x_{ij} \ + \ x_{ji} \ \leq \ 1, \ \ \forall\ i, j \ \in \ N$$

$$EC_{ij} \ \leq \ E_i, \ \ \forall\ i \ \in \ N$$

$$x_{ij} \in 0, 1$$

## IV. Security-Aware Optimization Formulation

We apply security-aware constraints to the routing optimization problem in order to improve security in IoT networks [14]. The following is the definition of the objective function that combines network performance and security.

$$Minimize\ F = \ w_1.ETX + \ w_2.LT + \ w_3.EC - w_4.SI \quad (2)$$

Where $w_1$, $w_2$, $w_3$, and $w_4$ are the respective weights assigned to $ETX$, $LT$, $EC$, and the security index ($SI$), which quantifies the resilience of the network against attacks.

### A. Security and Attack Analysis

IoT networks are extremely susceptible to different kinds of cyberattacks [13] that take advantage of resource constraints and routing flaws. Specifically, by absorbing all packets and preventing them from reaching their destination, Blackhole attacks [20] interfere with communication. Wormhole attacks cause significant route diversion by establishing a tunnel between two malevolent nodes in order to intercept and after communications. By deceiving trustworthy nodes into sending packets via a compromised node, sinkhole [10] attacks dramatically raise network latency and energy usage. Selective forwarding attacks make it more difficult to identify them by dropping important packets while forwarding others. By increasing the Expected Transmission Count, Latency and Energy Consumption, these attacks collectively degrade network performance.

Our architecture has anomaly detection methods that continuously track changes in routing behavior in order to combat these attacks. The security-aware optimization ensures routing pathways do not include compromised nodes, and energy-efficient, low-latency routes are prioritized.

### B. Security Index (SI)

We define a Security Index ($SI$) that takes into account the likelihood of attack detection ($D_A$) and the effect of the attack on routing reliability in order to guarantee secure routing.

$$SI = \sum_{i,j \in E} (D_{A_{ij}} \times R_{ij}) \quad (3)$$

Where:

- $D_{A_{ij}}$ indicated the likelihood of finding a link attack $(i, j)$, calculated based on anomaly detection methods .
- $R_{ij}$ represents the routing reliability of link $(i, j)$, which is inversely proportional to the number of compromised nodes.

### C. Security-Aware Constraints

To mitigate routing attacks, we introduce additional constraints:

**Attack Avoidance Constraint**

$$\sum_{(i,j)\in E} x_{ij} \cdot C_{ij} \leq T_{max} \tag{4}$$

Where: - $C_{ij}$ is a binary variable indicating whether a node $(i, j)$ is identified as compromised (1) or safe (0). - $T_{max}$ is a predefined threshold limiting the number of compromised nodes in the path.

**Secure Energy Constraint**

$$EC_{ij} + \sum_{k} ProcessingEnergy_k \leq E_i - E_{safe}, \quad \forall i \in N \tag{5}$$

Where:

- $E_{safe}$ is an energy buffer set aside to guard against malicious energy depletion.
- This limitation prevents attack-induced routing changes from causing nodes to prematurely exhaust their energy.

### D. Final Optimization Problem Formulation

Integrating security considerations, the final optimization model is formulated as:

$$\begin{aligned} Minimize \quad F = \sum_{i,j\in E} \Big( & w_1 \cdot ETX_{ij} + w_2 \cdot LT_{ij} \\ & + w_3 \cdot EC_{ij} - w_4 \cdot SI_{ij} \Big) \cdot x_{ij} \end{aligned} \tag{6}$$

Subject to:

$$\sum_{j\in N} x_{ij} = 1, \quad \forall i \in N \tag{7}$$

$$x_{ij} + x_{ji} \leq 1, \quad \forall i, j \in N \tag{8}$$

$$EC_{ij} \leq E_i - E_{safe}, \quad \forall i \in N \tag{9}$$

$$\sum_{(i,j)\in E} x_{ij} \cdot C_{ij} \leq T_{max} \tag{10}$$

$$x_{ij} \in \{0, 1\} \tag{11}$$

## V. Metaheuristic Methods for Routing Optimization in IoT Networks

Optimization methods that draw inspiration from physical, biological,or natural phenomena are known as metaheuristic algorithms [18]. They are employed to resolve complicated issues when precise methods are not feasible because of computational complexity. Metaheuristics [12] as opposed to exact algorithms produce high-quality approximations in a reasonable amount of time but do not ensure global optimality. Among the most popular algorithms in the field of IoT network optimization [9], we have used, PSO (Particle Swarm Optimization), MILP (Mixed-Integer Linear Programming), ARS2A (Adaptive Random Search with Two-Step Adjustment and Simulated Annealing).

### A. Algorithms Used

*1) Particle Swarm Optimization:* PSO [24] is modeled after how schools of fish or swarms of birds behave collectively. Each particle represents a good solution and adjusts its position according to its own experience and that of the other particles. The updating of positions is impacted by the best results observed individually and collectively.

**Key benefits :**

- Easy to implement
- Rapid convergence for certain types of problem
- Good exploration of the search space

*2) Mixed-Integer Linear Programming:* MILP [23] is a precise method that formulates a problem as linear constraints with continuous integer variables using mathematical models. Although it guarantees optimal solutions, it quickly becomes impractical for large networks due to its exponential complexity.

**Key benefits :**

- Optimality guarantee
- Suitable for small networks with limited resources
- Provides a benchmark for comparing heuristic solutions

*3) Simulated Annealing:* Simulated Annealing [22] is inspired by the process of metal cooling to avoid local minima, the algorithm investigates solutions by momentarily tolerating declines in solution quality. As the temperature drops, the likelihood of accepting a less-than-ideal solution gradually diminishes.

**Key Benefits**

- Avoid local minima with controlled random exploration
- Good flexibility for a wide range of problems
- Convergence controlled by cooling function

*4) Adaptive Random Search with Two-Step Adjustment (ARS2A):* Algorithm ARS2A is based on adaptive random search combined with two-stage fitting. It is effective for problems where the search space is large and non-linear.

**Key Benefits**

- Adaptability and flexibility in exploration
- Lightweight calculation approach
- Suitable for non-differentiable problems

These different metaheuristics offer various approaches for optimizing routing in IoT networks. While MILP provides optimal but computationally expensive solutions, heuristics such as PSO, ARS2A and Simulated Annealing deliver approximate results in a fair amount of time. Certain network constraints, including size dynamics, and resource availability.

### *B. Dataset Configurations for Metaheuristics Techniques and Security*

Metaheuristics algorithms [12], [25] are essential for optimizing routing in IoT networks by improving latency, energy consumption and transmission efficiency. This study compares several approaches, including PSO, MILP, ARS2A and Simulated Annealing, on networks of 100 and 150 nodes. The evaluation focuses on optimization capability, convergence and adaptability to topological variations. The analysis highlights the strengths and limitations of each method, helping to identify the most effective strategies for stable, energy-efficient routing in IoT networks [2].

TABLE I. SHAPES OF DATA SETS FOR DIFFERENT SIMULATIONS

| Simulation | Train Data Shape | Test Data Shape |
|---|---|---|
| 100 nodes | (80, 3) | (20, 3) |
| 150 nodes | (3392, 3) | (848, 3) |

The simulation datasets for 100 and 150 nodes were chosen to reflect both moderate and large-scale IoT environments, which are commonly deployed in smart cities and industrial monitoring. These configurations allow for robust evaluation of routing performance and scalability under various network sizes and threat levels (see Table I).

### *C. Implementation of Metaheuristics Techniques*

This section presents a Metaheuristics Techniques framework for minimizing transmission and energy costs in IoT networks.

This algorithm (Algorithm 1) optimizes routing in an IoT network while integrating security constraints to mitigate attacks. It starts with an initialization of network parameters and a risk assessment using an attack detection matrix. Next, it solves an optimization problem that minimizes a score combining ETX, latency, energy consumption and attack impact. Finally, it selects and deploys secure routing, guaranteeing a balance between network performance and protection.

This algorithm (Algorithm 2) applies simulated annealing to optimize several parameters of an IoT network, including ETX, latency and energy consumption. It starts with a random initial solution and evaluates its score using an objective function. At each iteration, it generates a neighboring solution, compares its score with the current solution and accepts it if it is better or with a certain probability according to the Metropolis criterion. The temperature is gradually reduced to refine the optimization. At the end of the iterations, the algorithm returns the best solution found, offering an optimal balance between routing, latency and energy consumption in an IoT environment.

**Algorithm 1** Security-Aware Routing Optimization for IoT Networks

**Input :** Network topology $G(N, E)$, attack detection matrix $D_A$, reliability matrix $R$, weights $w_1, w_2, w_3, w_4$, node energy $E_i$, max compromised threshold $T_{max}$.

**Output :** Optimized secure routing path minimizing $F$ under security constraints.

**/* Step 1: Initialization */** Normalize network parameters, initialize metrics Compute initial $ETX$, $LT$, and $EC$ for $(i, j) \in E$

**/* Step 2: Security Evaluation */** Compute $SI_{ij} = D_{A_{ij}} \times R_{ij}$ for $(i, j) \in E$

**/* Step 3: Routing Optimization */** Solve:

$$\min F = \sum_{(i,j)\in E} \left(w_1 ETX_{ij} + w_2 LT_{ij} + w_3 EC_{ij} - w_4 SI_{ij}\right) x_{ij} \tag{12}$$

Subject to:

$$\sum_j x_{ij} = 1, \quad x_{ij} + x_{ji} \leq 1, \quad EC_{ij} \leq E_i - E_{safe}, \tag{13}$$

$$\sum_{(i,j)\in E} x_{ij} C_{ij} \leq T_{max}, \quad x_{ij} \in \{0, 1\} \tag{14}$$

**/* Step 4: Route Selection and Deployment */** Extract and deploy optimized routing path Monitor network and adapt routing if needed **return** Optimized path

The PSO algorithm (Algorithm3) optimizes ETX, latency and energy metrics by adjusting the positions and speeds of a swarm of particles to minimize an objective function. Each particle updates its position according to its best score and the best overall solution found by the group. Thanks to its balance between exploration and exploitation, PSO enables rapid convergence towards an optimized solution, improving routing, latency and energy management in an IoT network.

Algorithm 4 demonstrate the ARS2A (Adaptive Random Search with Two-Step Adjustment) algorithm optimizes ETX, latency and energy metrics by exploring different solutions in a random, adaptive way. It starts with a random initial solution, then generates two candidate solutions at each iteration, selecting the best one to progressively improve the optimization. The algorithm dynamically adjusts its learning rate through adaptive updating, enabling faster convergence towards an optimal solution. This approach ensures an effective balance between minimizing latency, reducing energy consumption and optimizing routing in an IoT network.

The MILP (Mixed-Integer Linear Programming) algorithm (Algorithm 5) simultaneously optimizes ETX, latency and energy consumption by solving a constrained linear programming problem. It aims to minimize latency and energy consumption, while respecting the constraints defined by ETX to ensure efficient routing. The algorithm uses an optimization solver to find the optimal solution, then checks its feasibility before extracting the optimized mean values of the metrics. If it

**Algorithm 2** Simulated Annealing for Multi-Objective Optimization

**Inputs:**

- Initial Temperature $T_{initial}$
- Cooling rate $\alpha$;
- Maximum number of iterations $MaxIter$;
- Solution size (number of nodes) $N$;
- Dataset with metrics: $ETX, Latency(ms), EC(J)$;

**Outputs:**

- Optimal solution $S_{best}$;
- Optimal values of metrics (ETX, Latency, Consumed Energy);

**Begin Simulated Annealing Algorithm**

**/* Initialization */**
Initialize current solution: $S_{current} \leftarrow$ Random selection of $N$ nodes;
Compute current score: $Score_{current} \leftarrow OBJECTIVE\_FUNCTION(S_{current})$;
Set $S_{best} \leftarrow S_{current}$, $Score_{best} \leftarrow Score_{current}$;

**for** *iteration* $\leftarrow 1$ ***to*** $MaxIter$ **do**
  **/* Neighbor Generation */**
  Generate neighbor solution: $S_{neighbor} \leftarrow NEIGHBOR\_SOLUTION(S_{current})$;
  Compute neighbor score: $Score_{neighbor} \leftarrow OBJECTIVE\_FUNCTION(S_{neighbor})$;

  **/* Metropolis Criterion */**
  **if** $Score_{neighbor} < Score_{current}$ ***or*** $random(0,1) < exp\left(\frac{Score_{current} - Score_{neighbor}}{T_{initial}}\right)$ **then**
    Set $S_{current} \leftarrow S_{neighbor}$, $Score_{current} \leftarrow Score_{neighbor}$;

    **/* Best Solution Update */**
    **if** $Score_{current} < Score_{best}$ **then**
      Set $S_{best} \leftarrow S_{current}$, $Score_{best} \leftarrow Score_{current}$;
    **end**
  **end**
  **/* Temperature Update */**
  Update temperature: $T_{initial} \leftarrow \alpha \times T_{initial}$;
**end**

**/* Return Results */**
Return optimal solution $S_{best}$ and metrics (ETX, Latency, Consumed Energy);
**End Simulated Annealing Algorithm**

make require parameter adjustments. This approach guarantees rigorous and efficient optimization, suitable for IoT networks requiring fast, energy-efficient routing.

## VI. Results and Discussion

### A. Experimental Environment

The tests were conducted on a device with an Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz, 8 GB RAM, and a 64-bit Windows system. Python was used to implement categorization methods on Jupyter Notebook, with libraries such as pandas (1.5.3), matplotlib, seabron and random. Dependencies and

**Algorithm 3** Particle Swarm Optimization for Multi-Objective Optimization

**Inputs:**

- Number of particles $num\_particles$;
- Number of iterations $num\_iterations$;
- Inertia weight $w$;
- Personal acceleration coefficient $c_1$;
- Global acceleration coefficient $c_2$;
- Dataset with metrics: $ETX, Latency, ConsumedEnergy$;

**Outputs:**

- Optimal solution $S_{best}$;
- Optimal values of metrics (ETX, Latency, Consumed Energy);

**Begin PSO Algorithm**

**/* Initialization */**
Initialize particle positions randomly: $positions \leftarrow$ random indices of dataset nodes;
Initialize particle velocities randomly;
Evaluate particles using $OBJECTIVE\_FUNCTION$;
Set personal best positions $personal\_best\_positions \leftarrow positions$;
Set global best position $S_{best} \leftarrow$ position of best particle;

**for** *iteration* $\leftarrow 1$ ***to*** $num\_iterations$ **do**
  **for** *particle* $i \leftarrow 1$ ***to*** $num\_particles$ **do**
    **/* Velocity and Position Update */**
    Generate random numbers $r_1, r_2 \in [0,1]$;
    Update velocity:
    $velocity_i \leftarrow w \cdot velocity_i + c_1 \cdot r_1(personal\_best_i - position_i) + c_1 \cdot r_2(S_{best} - position_i)$;
    Update position:
    $position_i \leftarrow position_i + velocity_i$;
    Ensure valid positions: keep $position_i$ within bounds;

    **/* Evaluation and update */**
    Evaluate particle position:
    $Score_i \leftarrow OBJECTIVE\_FUNCTION(position_i)$;
    **if** $Score_i < Score_{personal\_best_i}$ **then**
      Update personal best for particle $i$:
      $personal\_best_i \leftarrow position_i$;
    **end**
    **if** $Score_i < Score_{global\_best}$ **then**
      Update global best position: $S_{best} \leftarrow position_i$;
    **end**
  **end**
**end**

**/* Return Results */**
Return optimal solution $S_{best}$ and metrics (ETX, Latency, Consumed Energy);
**EndAlgorithm**

**Algorithm 4** Adaptive Random Search with Two-Step Adjustment for Multi-Objective Optimization

**Inputs:**

- Number of iterations $num\_iterations$;
- Solution size $solution\_size$;
- Dataset with metrics: $ETX$, $Latency$, $Consumed\ Energy$;

**Outputs:**

- Optimal solution $S_{best}$;
- Optimal values of metrics ($ETX$, $Latency$, $Consumed\ Energy$);

**Begin ARS2A Algorithm**

**/* Initialization */**
Initialize a random solution:

$$S_{current} \leftarrow \{x_i \mid i \in \text{random subset of nodes}\} \tag{15}$$

Compute the initial objective function value:

$$Score_{current} = w_1 \cdot ETX(S_{current}) + w_2 \cdot LT(S_{current}) + w_3 \cdot EC(S_{current}) \tag{16}$$

Set $S_{best} \leftarrow S_{current}$, $Score_{best} \leftarrow Score_{current}$;

**for** *iteration* $\leftarrow 1$ ***to*** $num\_iterations$ **do**

**/* Generate two random candidate solutions */**
Select two random solutions $S_{candidate1}$ and $S_{candidate2}$;
Compute their objective function values:

$$Score_{candidate1} = w_1 \cdot ETX(S_{candidate1}) + w_2 \cdot LT(S_{candidate1}) + w_3 \cdot EC(S_{candidate1}) \tag{17}$$

$$Score_{candidate2} = w_1 \cdot ETX(S_{candidate2}) + w_2 \cdot LT(S_{candidate2}) + w_3 \cdot EC(S_{candidate2}) \tag{18}$$

**/* Selection Step */**
**if** $Score_{candidate1} < Score_{candidate2}$ **then**

$$S_{new} \leftarrow S_{candidate1}, \quad Score_{new} \leftarrow Score_{candidate1} \tag{19}$$

**end**
**else**

$$S_{new} \leftarrow S_{candidate2}, \quad Score_{new} \leftarrow Score_{candidate2} \tag{20}$$

**end**

**/* Update Best Solution */**
**if** $Score_{new} < Score_{best}$ **then**

$$S_{best} \leftarrow S_{new}, \quad Score_{best} \leftarrow Score_{new} \tag{21}$$

**end**

**/* Adaptive Learning Rate Adjustment */**
Introduce an adaptive learning factor to improve convergence:

$$S_{best} \leftarrow S_{best} - \alpha \cdot \nabla F(S_{best}) \tag{22}$$

where $\nabla F(S_{best})$ represents the local gradient estimation of the objective function.

**end**

**/* Return Results */**
Return optimal solution $S_{best}$ and metrics ($ETX$, $Latency$, $Consumed\ Energy$);
**EndAlgorithm**

**Algorithm 5** MILP for Multi-Objective Optimization

**Inputs:**

- Dataset containing metrics: $ETX, Latency, ConsumedEnergy$;
- Objective coefficients $c$ (minimization of Latency + Energy);
- Constraints matrix $A$ (based on ETX);
- Constraint bounds $b$;
- Solution bounds;

**Outputs:**

- Optimal solution $S_{best}$;
- Optimal average values of metrics (ETX, Latency, Consumed Energy);

**Begin MILP Algorithm**

**/* Solve MILP Problem */**
Solve the linear programming optimization:
Minimize $c^T x$
Subject to constraints:
$A \times x \leq b$, $0 \leq x_i \leq 1 \quad \forall i \in$ solutions indices;
Use optimization solver (e.g., *linprog* method "highs");

**/* Check solution feasibility and optimality */**
**if** *Solution is feasible and optimal* **then**
Extract best solutions' metrics: ETX, Latency, Consumed Energy;
Compute average values over the best solutions found;
**end**
**else**
Report failure and suggest parameter adjustment;
**end**

**/* Return Results */**
Return optimal solution $S_{best}$ and metrics (ETX, Latency, Consumed Energy);
**EndAlgorithm**

tools were managed using Anaconda, which facilitates the implementation and management of metaheuristics techniques.

### *B. Performance of Algorithms Across all Simulations*

In order to assess the effects of metaheuristics techniques and secure optimization, this study simulated IoT networks with 100 and 150 nodes. The algorithms successfully predicted ETX, latency, and energy consumption,enabling performance comparisons. Table II and Table III demonstrate the potential of metaheuristics techniques in optimizing IoT networks and propelling future developments. Table IV demonstrate a parameters of PSO, MILP, ARS2A, and Simulated Annealing.

TABLE II. COMPARISON OF PSO, MILP, ARS2A AND SIMULATED ANNEALING RESULTS ON 100 NODES

| Algorithm | ETX | Latency (ms) | Consumed Energy (J) |
|---|---|---|---|
| PSO | 3.2791 | 81.7157 | 1.5756 |
| MILP | 2.9884 | 81.7157 | 10.5672 |
| ARS2A | 1.3481 | 12.2719 | 3.5139 |
| Simulated Annealing | 4.7602 | 10.5672 | 1.5756 |

TABLE III. COMPARISON OF PSO, MILP, ARS2A AND SIMULATED ANNEALING RESULTS ON 150 NODES

| Algorithm | ETX | Latency (ms) | Consumed Energy (J) |
|---|---|---|---|
| PSO | 1.70 | 0.34 | 0.54 |
| MILP | 1.10 | 0.12 | 0.85 |
| ARS2A | 1.28 | 0.15 | 1.45 |
| Simulated Annealing | 2.55 | 3.22 | 0.75 |

TABLE IV. PARAMETERS OF PSO, MILP, ARS2A, AND SIMULATED ANNEALING PARAMETERS

| Parameter | PSO | MILP | ARS2A | SA |
|---|---|---|---|---|
| Iterations | 50 | N/A | 1000 | 2000 |
| Population Size | 20 | N/A | N/A | 10 |
| Inertia (w) | 0.5 | N/A | N/A | N/A |
| C1, C2 | 1.5, 1.5 | N/A | N/A | N/A |
| Cooling Rate | N/A | N/A | N/A | 0.995 |
| Selection | Best global | Min(Lat+Energy) | Best of 2 | Probabilistic |
| Best ETX | Dyn. (X-Y) | Top 10 Avg. | Random Best | Selected Nodes |
| Best Latency (ms) | Dyn. (X-Y) | Top 10 Avg. | Random Best | Selected Nodes |
| Best Energy (J) | Dyn. (X-Y) | Top 10 Avg. | Random Best | Selected Nodes |
| Complexity | O(n × i) | NP-hard | O(i) | O(i) |

The performance of the optimization algorithms is closely tied to their parameter configurations. For instance, PSO relies on the inertia weight and acceleration coefficients to balance exploration and exploitation. Simulated Annealing's behavior is governed by its cooling rate and temperature schedule, which affect convergence speed and escape from local minima. MILP depends on solver precision and constraint bounds, while ARS2A dynamically adjusts its learning rate to adapt during iterations. These parameters were fine-tuned through preliminary experimentation to ensure effective performance across different scenarios.

### C. Simulation of Attacks

*1) Correlation Matrix:* The correlation matrices for the 100 (Fig. 1)- and 150-node (Fig. 2) datasets show how the ETX, Latency and Energy Consumption metrics relate to one another. In the 150-node dataset, correlations are almost zero, demonstrating that increasing the number of nodes reduces the dependency between these parameters, recommending improved distribution for routing. On the other hand, in the 100-node dataset, slight correlations are observed, notably between ETX and energy consumption (-0.13), indicating that routing performance has a greater influence on energy consumption in a less dense network. These findings demonstrate that routing dynamics and energy optimization are impacted by network scale, requiring network-size-specific strategies.

*2) Distribution of Attacks:* Fig. 3 shows the distribution of assaults in the revised dataset is displayed in the graph (figure). The majority of connections are evidently normal, however the most common assaults are Sinkhole and Blackhole, which are Known to interfere with routing by intercepting and dropping data packets. Although they are less common other attacks like Flooding, Grayhole, and Selective Forwarding also impact packet transit by overloading the network or causing delays. Finally, Sybil and Wormhole attacks, although less frequent, can have significant consequences by manipulating network topology and creating false routes. This distribution emphasizes the variety of network risks and the necessity of strong detection and mitigation strategies.

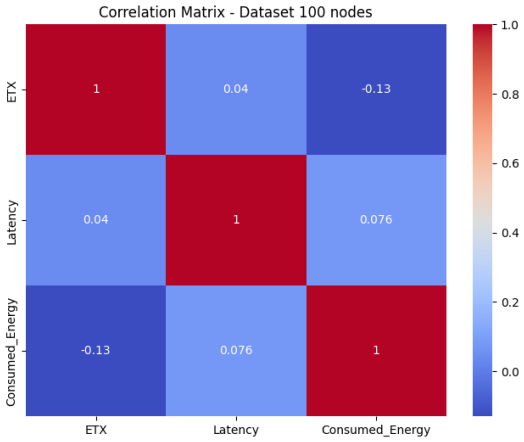


Fig. 1. Correlation matrix for 100 nodes.

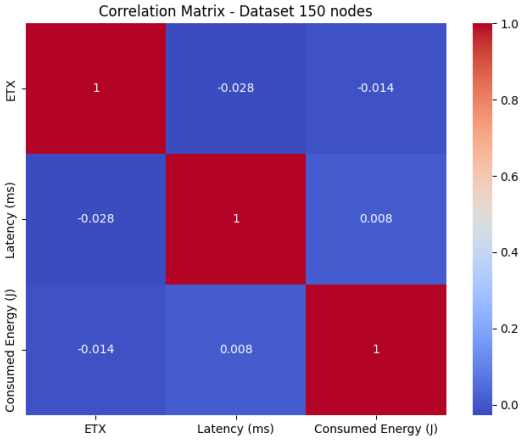


Fig. 2. Correlation matrix for 150 nodes.

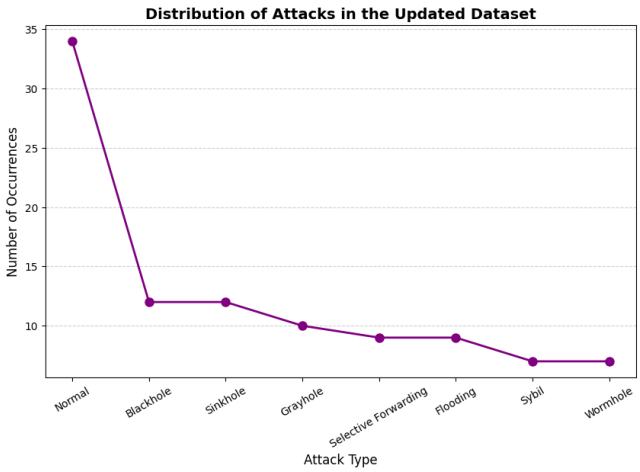


Fig. 3. Attacks.

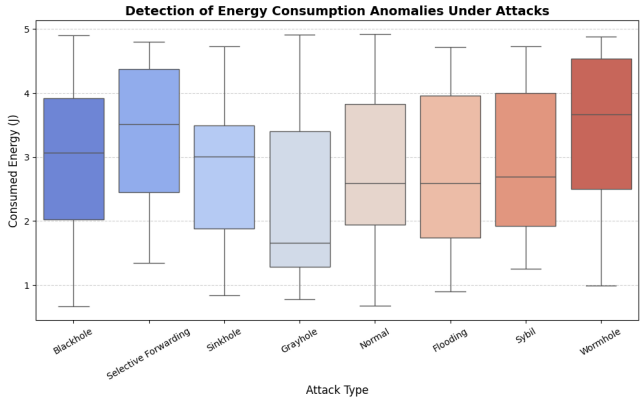


Fig. 4. Detection of energy consumption anomaly under attacks.

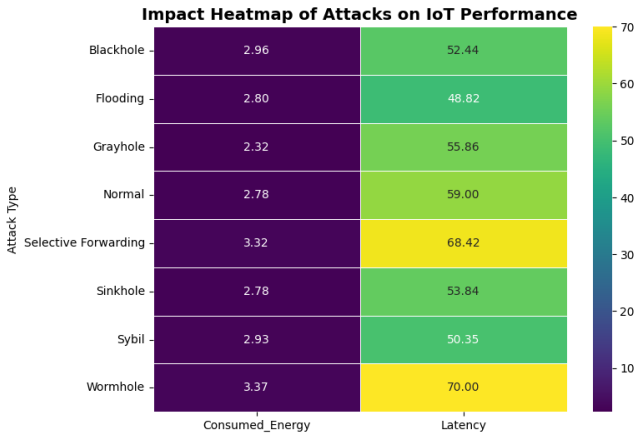


Fig. 5. Impact attacks on IoT.

*3) Detection of energy consumption anomaly under attacks:* Fig. 4 suggest that the differences in energy consumption under different types of attack are depicted in the box graphic. Given that they interfere with packet routing and diminish network activity, it is evident that Blackhole and Grayhole attacks exhibit a comparatively lower median energy consumption. On the other hand,Wormhole and Selective Forwarding assaults use more energy, most likely because of the overload causes by packet hijacking or redundant transmissions. As a standard for comparison, normal network operation exhibits low energy use. The higher power usage during Flooding and Sybil attacks indicates that they put a heavy burden on the network by causing excessive traffic or skewing routing choices. The findings highlight how critical energy-efficient security measures are for identifying and reducing anomalies brought on by intrusions in Internet of Things networks.

*4) Impact heatmap attacks on IoT:* Fig. 5 shows the heatmap how various attacks affect an IoT networks latency and energy usage. The network is significantly slowed down by the Wormhole and Selective Forwarding attacks, which have the largest latencies at 70.00 and 68.42ms, respectively. By contrast, the Flooding attack has a relatively lower latency (48.82 ms), but can still affect network reliability. In terms of energy consumption, the highest values were observed by the Selective Forwarding and Wormhole assaults (3.37J and 3.32J, respectively), suggesting network overload due to excessive transmissions or packet hijacking. In contrast, Attacks by flooding and grayhole us less energy, which suggests that they have on resource use. These findings highlight the fact that some attacks specifically, Wormhole and Selective Forwarding are especially harmful since they affect latency and energy consumption simultaneously, necessitating efficient detection and mitigation techniques.

*5) Latency variability under different attacks:* The above diagram (Fig. 6) shows how latency varies in an IoT network under various attacks. It is evident that certain assaults, such as Grayhole and Selective Forwarding, exhibit a wide range of latency values, occasionally reaching extremely high levels, signifying serious network instability. The Wormhole attack displays a generally higher and more concentrated latency, suggesting a systematic impact on packet delay. Conversely, the Blackhole and Sinkhole attacks show more moderate latency, although their impact remains significant. Normal network

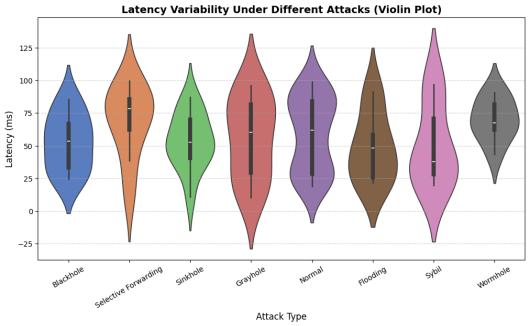


Fig. 6. Latency variability under different attacks (Violin Plot).

operation indicates a more even distribution, with generally lower and more stable latency. These results demonstrate how attacks can have varying effects on latency; some generate one-time spikes in latency, while others result in chronic latency, necessitating modified mitigation techniques.

## D. Results of 100 Nodes

*1) PSO:* Fig. 7 indicate the Particle Swarm Optimization algorithms convergence when used for IoT network security is depicted in the graph. Around the 35 iteration, we see a sharp decline, suggesting a significant improvement in the solution, after an initial period of stagnation during with which the objective function stays constant. After this descent, the score stabilizes and no longer varies until the end of the iterations, suggesting that PSO has reached an optimal solution relatively early. With a strong capacity to explore and take advantage of the search area, this quick and steady convergence shows how well PSO optimizes routing and safety parameters. These results indicate the value of PSO for Internet of Things applications that need to converge quickly while maintaining peak performance.

*2) MILP:* Fig. 8 shows how the MILP technique optimized the distribution of parameters, with an emphasis on ETX, latency, and Energy Consumption. Latency shows high variability, with values ranging up to 100 ms, indicating that the optimization attempts to minimize latency, but with some dispersion. The energy usage and ETX measures, on the other hand, are significantly more consistent and fluctuate

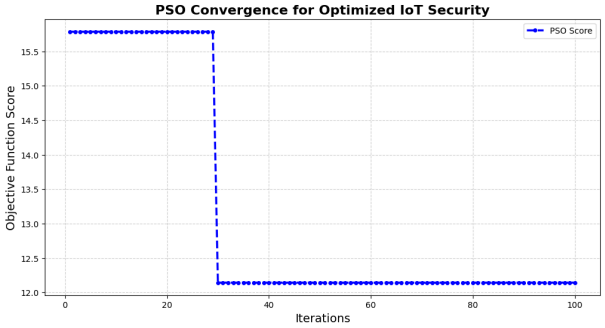


Fig. 7. Results of PSO.

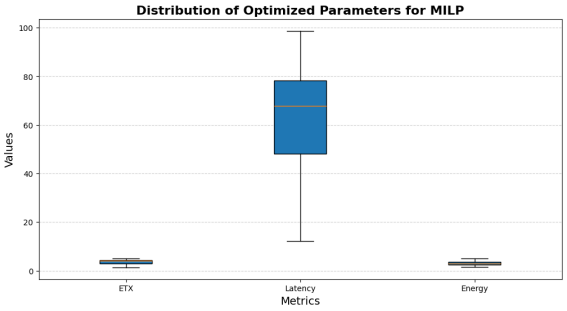


Fig. 8. Results of MILP.

less, indicating that MILP has identified ideal values for these parameters.

*3) Simulated annealing:* The ideal values that the simulated Annealing process produced on a typical sample of simulated IoT network nodes that were being attacked are shown in Fig. 9. The overall scores steady change across the algorithms iterations is depicted in Fig. 10. Particularly after 1000 iterations; there is a noticeable drop in score, indicating a clear and effective convergence towards an ideal solution. Finally, Fig. 11 shows how each parameters (ETX, latency, and energy consumption). This visualization particularly highlights the significant and stable reduction in latency, demonstrating that the algorithm gives this statistic top priority in order to maximize the IoT networks overall quality. Additionally, the stability observed for ETX.

*4) ARS2A:* The convergence of the ARS2A algorithms optimization score is depicted in Fig. 12. In the initial iterations,the score rapidly drops from 26 to about 12, before stabilizing after 400 iterations. This pattern indicates that the algorithm is quickly identifying the best answer,which lowers network in efficiencies and boosts efficiency. Fig. 13 shows the evolution of key metrics: ETX, latency and energy consumption. Routing Optimization is indicated by a significant drop in latency before it stabilizes. A similar pattern is seen in energy usage, which shows a decline in energy expenses. Lastly, ETX stays steady, indicating that routing reliability has improved.

## E. Results of 150 Nodes

*1) PSO:* The first figure (Fig. 14) illustrates the PSO algorithms show convergence and effective solution optimization over the period of repetitions. This stability demonstrates

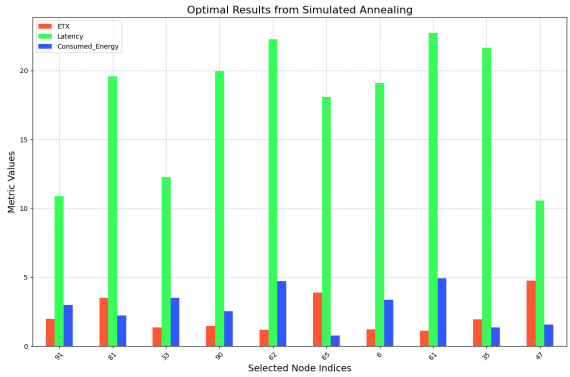


Fig. 9. Optimal results from simulated annealing.

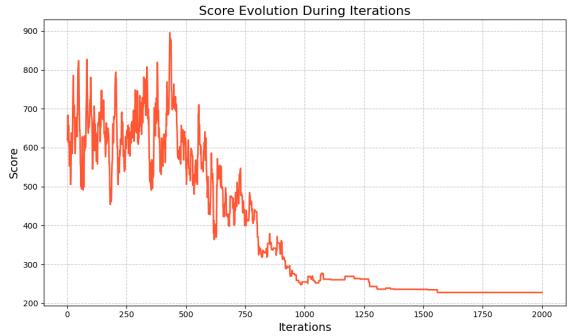


Fig. 10. Score evolution during iterations.

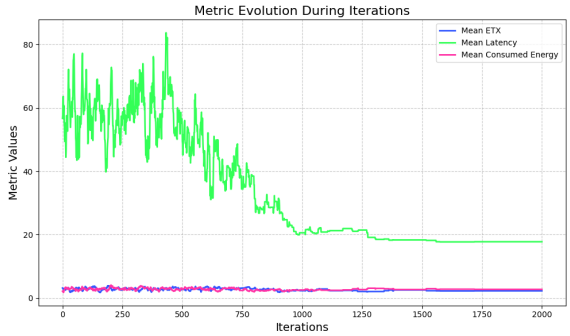


Fig. 11. Metric evolution during iterations.

how PSO progressively modifies particle placements to reduce inaccuracy. The effect of PSO on three important metrics: ETX, Latency, Energy Consumption, is depicted in Fig. 15. When delay is reduced and ETX reaches a high value, transmission efficiency is increased. Energy consumption remains moderate, proving that PSO optimizes routing by maintaining a balance between performance and energy consumption.

*2) MILP:* The convergence of MILP is displayed in Fig. 16 based on various optimization options (priority over ETX, latency, energy consumption). Every configuration gradually lowers the objective function score, but those that prioritize energy and active search show faster convergence, suggesting higher efficiency. Fig. 17 contrasts each configurations optimized ETX, latency, and energy usage metrics. While distinct goals allow targets optimization, highlighting the trade offs between performance and energy usage, balanced strategies produce comparable outcomes.

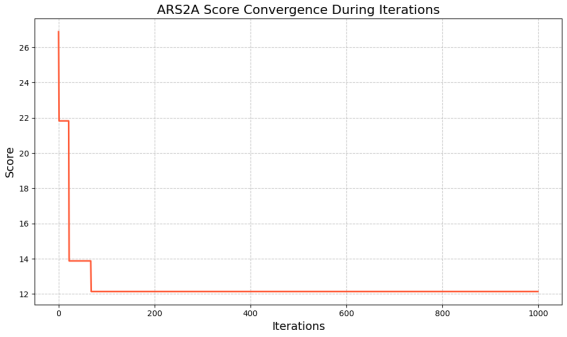


Fig. 12. ARS2A score convergence during iterations.

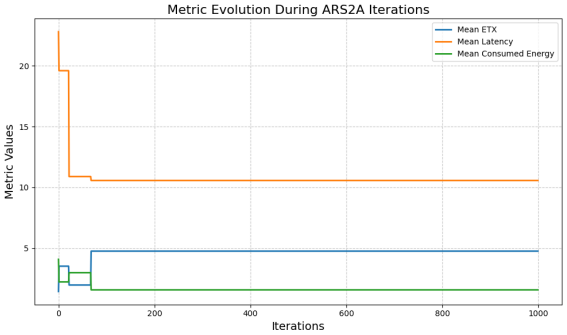


Fig. 13. Metric evolution during ARS2A iterations.

*3) Simulated Annealing:* The ETX, latency, Energy Consumption measures ideal values as determined by Simulated Annealing on an RPL-IoT network under assault are displayed in Fig. 18. The outcomes demonstrate a suitable balance between these variables, guaranteeing effective energy, Latency, and link quality control. With a steady increase in the overall score until stabilization after about 1200 iterations, Fig. 19 shows the algorithm convergence and demonstrates the optimizations resilience and effectiveness in spite of the dataset complexity. Finally, Fig. 20 details the evolution of metrics over the course of iterations, highlighting a marked reduction in latency and energy consumption.The ultimate stability of the curves demonstrates that Simulated Annealing can effectively handle several concurrent objectives, which qualifies it for use in IoT network security applications.

*4) ARS2A:* An instantaneous improvement in the solution is indicated by Fig. 21 sharp decline in the optimization score during the initial iterations.The curve stabilizes after 200 iterations indicating that ARS2A is effective and that the algorithm has attained an optimal minimum. The evolution of three important metrics: ETX, Latency and Energy depicted in Fig. 22. ETX exhibits dynamic route adjustment, fluctuating significantly before settling. After 300 rounds, latency steadily drops and stabilizes enhancing packet delivery. Similar trends are shown in energy usage, which has significantly decreased from the initial iterations

## VII. Discussion of the Results

Significant variations exist between these strategies in terms of efficiency and goal balance, according to the comparative analysis. Although MILP uses a lot of energy, it has the lowest

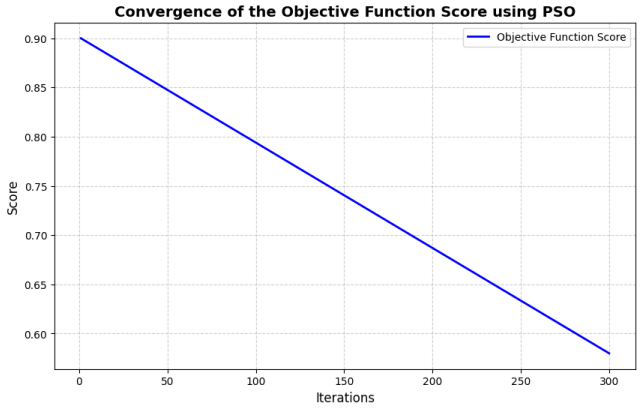


Fig. 14. Convergence of the objective function score using PSO.

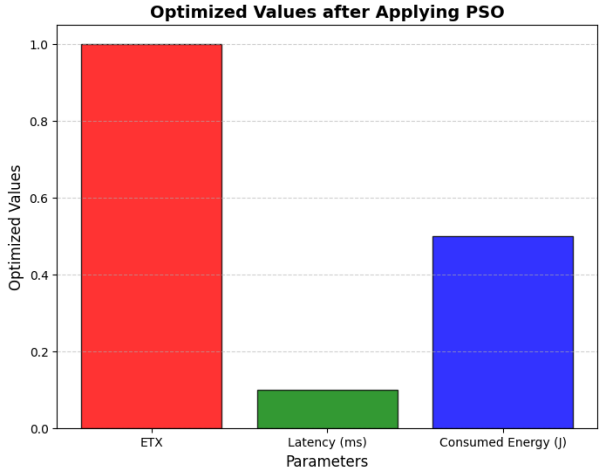


Fig. 15. Optimized values after applying PSO.

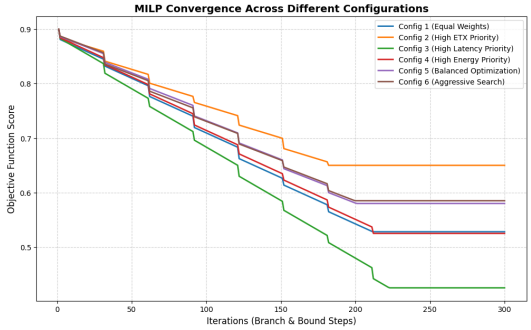


Fig. 16. MILP Convergence across different configurations.

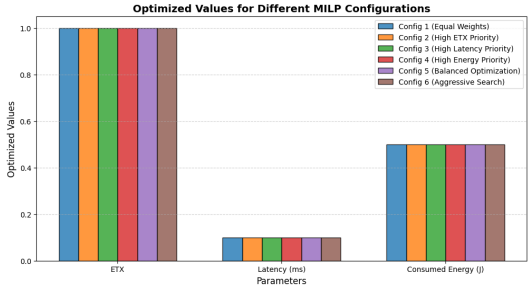


Fig. 17. Optimized values for different MILP configurations.

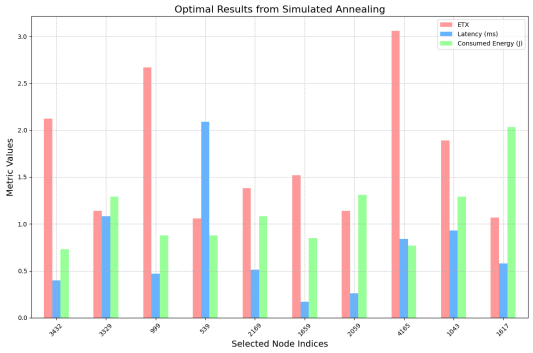


Fig. 18. Optimal results from simulated annealing.

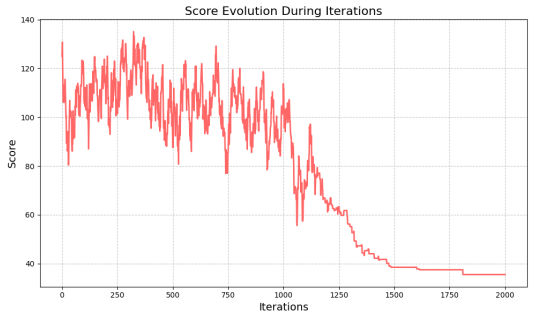


Fig. 19. Score evolution during iterations.

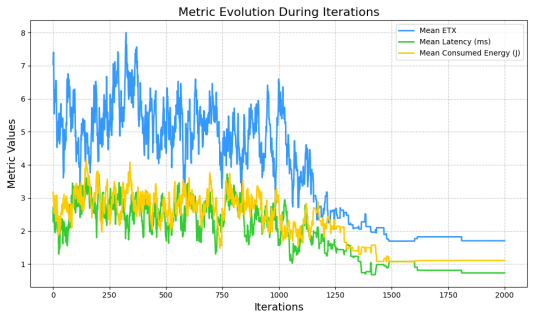


Fig. 20. Metric evolution during iterations.

latency which is essential for applications that need quick transmission. In certain configurations, PSO has high latency, but it effectively optimizes ETX by lowering the number of hops required to reach the destination, ARS2A is notable for its capacity to sustain low latency and moderate energy consumption providing a favorable trade-off between network lifetime and routing efficiency. Finally, Results from Simulated Annealing are competitive, especially on the 100-node network, where it manages to optimize latency and energy, although its ETX score is not the best, which may imply an increase in the number of intermediate transmissions. In contrast, ARS2A exhibits superior adaptability on a larger network with 150 nodes, stabilizing performance while preserving an effective trade-off between latency and energy consumption. Thus, According to the the study, ARS2A provides the best robustness and stability, especially on large-scale IoT networks. While MILP excels at minimizing latency. These finding imply that network constraints play a major in algorithm selection and that a hybrid strategy that combines the advantages of PSO and MILP may be the best way to balance quick response times,

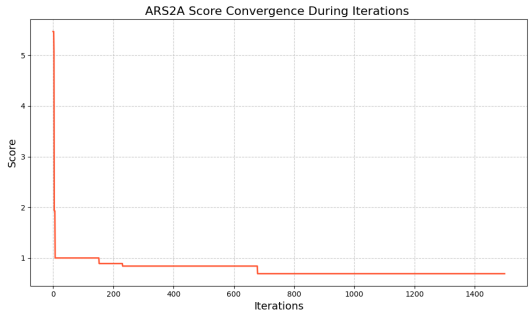


Fig. 21. ARS2A Score convergence during iterations.

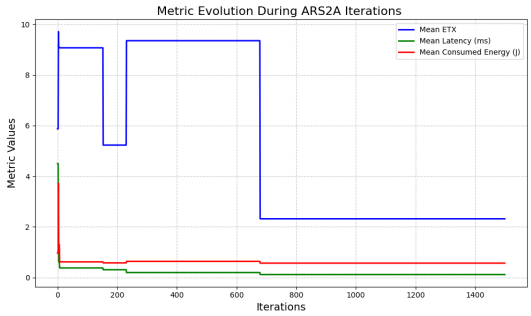


Fig. 22. Metric evolution during ARS2A iterations.

low energy costs, and effective routing.

## VIII. Conclusion

In this study, we compared PSO, MILP, ARS2A and Simulated Annealing on networks of 100 and 150 nodes. In order to explore various optimization strategies while integrating security considerations in the face of networks attacks.Routing optimization in RPL-based IoT networks is a crucial issue where energy efficiency, latency, and transmission reliability must be balanced to ensure network performance and resilience.

According to simulation results, MILP is the best option for applications needing quick, reliable routing because it excels at reducing latency. Nevertheless; this method uses more energy, which restricts its use in battery-powered networks. Though it comes at the cost latency, PSO efficiently optimizes transmission cost (ETX) by lowering the number of hops required to route data. One of the most well-balanced algorithms turned out to be ARS2A, maintaining good performance stability over different scenarios, with low latency and controlled energy consumption. While its ETX was not always ideal suggesting a greater number of retransmissions, Simulated Annealing distinguished itself for its resilience in simultaneously optimizing latency and energy.

The impact of Selective Forwarding, Sinkhole, and Blackhole attacks, which hinder data transmission and raise network energy consumption, has been lessened by the incorporation of routing security measures. By excluding compromised nodes from the routing process, overall algorithm performance was preserved despite the hostile environment. From an applied perspective, these results indicate that the selection of an optimization algorithm must be adapted to network constraints. For an environment requiring fast, reliable transmission, MILP

is a robust, albeit resource-intensive, solution. PSO and ARS2A seem like appropriate options in a setting where network lifetime is crucial since they provide improved energy management without sacrificing. Future work will focus on integrating reinforcement learning techniques with metaheuristics to further enhance autonomous decision-making in secure routing. Additionally, validating the framework on real-world IoT testbeds and extending support for heterogeneous networks will improve its adaptability and practical deployment.

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