Machine Learning Methods for Detecting Fake News: A Systematic Literature Review of Machine Learning Applications in Key Domains

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***Abstract*—Rapid digitisation in communication and online platform growth have transformed information dissemination and facilitated rapid access while simultaneously amplifying the spread of fake news. This widespread issue undermines public trust, destabilises political systems, and threatens economic stability. Machine learning techniques have been widely applied to fake news detection, but comparative analyses across specific domains such as health, politics, and economics remain limited. Existing reviews tend to focus on supervised learning methods, frequently excluding unsupervised and hybrid approaches, along with unique challenges and dataset requirements of each domain. This study conducted a systematic literature review of machine learning applications for detecting fake news across the three domains. The methodologies and metrics used were evaluated, while key challenges and opportunities were explored. The results revealed a strong reliance on supervised learning techniques, particularly in health-related contexts, where misinformation presented significant risks to public health outcomes. Deep learning methods were promising for processing complex data. Nonetheless, hybrid and unsupervised approaches were underexplored, which presented opportunities to address data scarcity and adaptability. Most datasets originated from social media platforms and news outlets. The common evaluation metrics included accuracy, but advanced measures were rarely applied, which indicated the possibility of enhancing such methods. Persistent challenges include poor data quality, bias, and ethical concerns highlighted the necessity for bias-mitigating algorithms and improved model interpretability. Specifically, economic misinformation has received less attention despite its potential to cause large-scale financial disruptions. This study highlighted that more effective, ethical, and context-specific machine learning solutions are needed to address fake news and enhance digital information credibility.**

Keywords*—Machine learning; fake news; systematic review; health; politics; economy

I. INTRODUCTION

Technological breakthroughs and the digital era have transformed global communication and news production, distribution, and consumption methods at incomparable rates. These advancements have been supported by prominent social media platforms and online news portals and cultivated a connected global community, which has facilitated the rapid dissemination of news across geographical and accessibility boundaries [1, 2]. Nevertheless, these positive advancements are accompanied by a corresponding negative regression. One of the most alarming examples of negative regression is increased fake news, which creates negative sociological situations. These situations range from decreased trust and reliability to election result manipulation and global health crises exacerbation [3-5].

Fake news in health, politics, and economics can lead to severe and negative outcomes. For example, spreading false health information establishes the basis for adverse outcomes. The recent indications include false narratives around the COVID vaccine, hydroxychloroquine efficiency as a cure, claims that bleach treats conditions, and smear campaigns against vaccines [6-8]. These fraudulent statements have caused public health issues, which have confused the public and encouraged it to adopt unsafe health practices, such as avoiding vaccinations after misleading information has been disseminated.

In politics, misinformation produces false perceptions and fosters public discontent against politicians and democracy, which distorts electoral outcomes. Misinformation is aimed at causing division, disseminating falsehoods about individuals and matters that damage reputations, disrupting discussions, and subsequently creating distrust against respected media outlets [9, 10]. Ultimately, misinformation is divisive and exacerbates conflict.

Fake news is also prevalent in economic news. Prevalent misinformation on the economy or inaccurate economic reporting induces stock market fluctuations, personal financial crises, and a deterioration of faith in financial assets. Furthermore, economic misinformation undermines investor trust and disrupts economic system stability.

Traditional methods for detecting fake news, such as manual fact-checking and rule-based detection, have been insufficient due to their inability to address the scale, speed, and complexity of modern misinformation [11, 12]. The current proliferation of fake news is broadly diverse, spreads rapidly, and is high-volume. Hence, an efficient and scalable generalized detection system has become necessary. Thus, machine learning has emerged as an effective tool among researchers and practitioners for addressing misinformation. The ability of machine learning to analyse enormous datasets, identify trends, and provide accurate predictions has been used in advanced automated solutions to identify fake news. These platforms use various techniques, which include natural language processing (NLP), sentiment analysis, and deep learning, to detect and classify fake news accurately [13, 14].

Although numerous studies have applied ML techniques to fake news detection, comparative reviews that assess the performance of these methods across specific domain such as health, politics, and economics remain limited. Moreover, existing reviews often emphasize supervised learning, frequently failing to consider unsupervised and hybrid approaches, as well as the distinct challenges and dataset requirements unique to each domain. Thus, this study conducted a comprehensive systematic literature review (SLR) to examine the application of machine learning techniques for detecting fake news detection across the health, politics, and economics domains.

This study synthesized the results to advance the development of more effective, ethical, and domain-specific solutions to address fake news. Specifically, three research questions (RQ) were addressed: 1) the machine learning approaches utilized within these domains was investigated to provide insights into their methodologies and domain-specific applications (RQ1); 2) the performance and effectiveness of these techniques were evaluated by analyzing the commonly used evaluation metrics (RQ2); 3) key trends, challenges, and opportunities in the field were identified, limitations in these approaches were highlighted, and potential future research directions were proposed (RQ3).

II. METHODOLOGY

A. Research Questions

This study explored the application of machine learning in identifying fake news across the health, politics, and economics domains, guided by the following Research Questions (RQs):

- RQ1: How is machine learning applied for detecting fake news in the health, political, and economics domains?
- RQ2: What are the evaluation metrics commonly used in the health, political, and economics domains?
- RQ3: What are the key trends, challenges, and future directions in the health, political, and economics domains?

B. Literature Search Strategy

The literature search was conducted using the Web of Science, Scopus, IEEE Xplore, and SpringerLink databases. The literature search was performed using a combination of keywords and Boolean operators to ensure comprehensive retrieval of relevant studies to fake news detection. Table I details the search terms used across the three domains.

TABLE I. THE SEARCH TERMS FOR IDETIFYING FAKE NEWS DETECTION ACCORDING TO THE DOMAIN

Domain	Search Term
Politics	((“fake news detection*” OR “misinformation”) AND (“social media”) AND (“politics” OR “bureaucracy”) AND (“machine learning*” OR “deep learning” OR “hybrid learning”))
Economy	((“fake news detection*” OR “misinformation”) AND (“social media”) AND (“economy”) AND (“machine learning*” OR “deep learning” OR “hybrid learning”))
Health	((“fake news detection*” OR “misinformation”) AND (“social media”) AND (“health” OR “healthcare” OR “medical care”) AND (“machine learning*” OR “deep learning” OR “hybrid learning”))

C. Inclusion and Exclusion Criteria

Table II outlines the inclusion and exclusion criteria applied to ensure the quality and relevance of the selected studies.

TABLE II. THE INCLUSION AND EXCLUSION CRITERIA

Inclusion	Exclusion
• Studies published in peer-reviewed journals or conferences; • Publications written in English; • Fully accessible articles; • Research focusing on the application of machine learning techniques for fake news detection in health, political, or economics domains; • Publications from the last 10 years to ensure relevance and reflect current trends and advancements.	• Non-peer-reviewed any articles; • Non-English publications; • Articles that are inaccessible and or lack full text; • Studies without a clear focus on machine learning applications in detecting fake news.

D. Study Selection and Screening

The study selection followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [15] (see Fig. 1). The studies were selected through identification (initial search results were exported to a reference management tool and duplicates were removed), screening (titles and abstracts were reviewed to identify potentially relevant studies), eligibility assessment (full-text articles were assessed against the inclusion and exclusion criteria), and inclusion (the remaining studies were selected for detailed analysis and synthesis).

E. Data Extraction and Screening

Data were extracted from the selected studies using a standardised data extraction form. The key information collected included:

- Publication type: The data source (whether published in a journal or presented at a conference);
- Domain-specific applications: The focus area of the fake news (categorised into health, politics, or economics domains);
- Research type: The methodological approach of the study (qualitative or quantitative research);

- Study objectives and contributions: The study goals and specific contributions;
- Dataset: The name and description of the fake news corpus used in the study;
- Data preparation and preprocessing: Details on any data cleaning, transformation, or preprocessing techniques applied to the dataset;
- Machine learning techniques used: A description of the machine learning algorithms or methods implemented in the study;
- Performance measures: The evaluation metrics used to assess the effectiveness of proposed machine learning models, such as accuracy, precision, and F-measure;
- Findings, limitations, and future work: Key insights from the study, the identified limitations, and recommendations for future research directions.

Appendix A presents the articles included in this systematic review (n = 173).

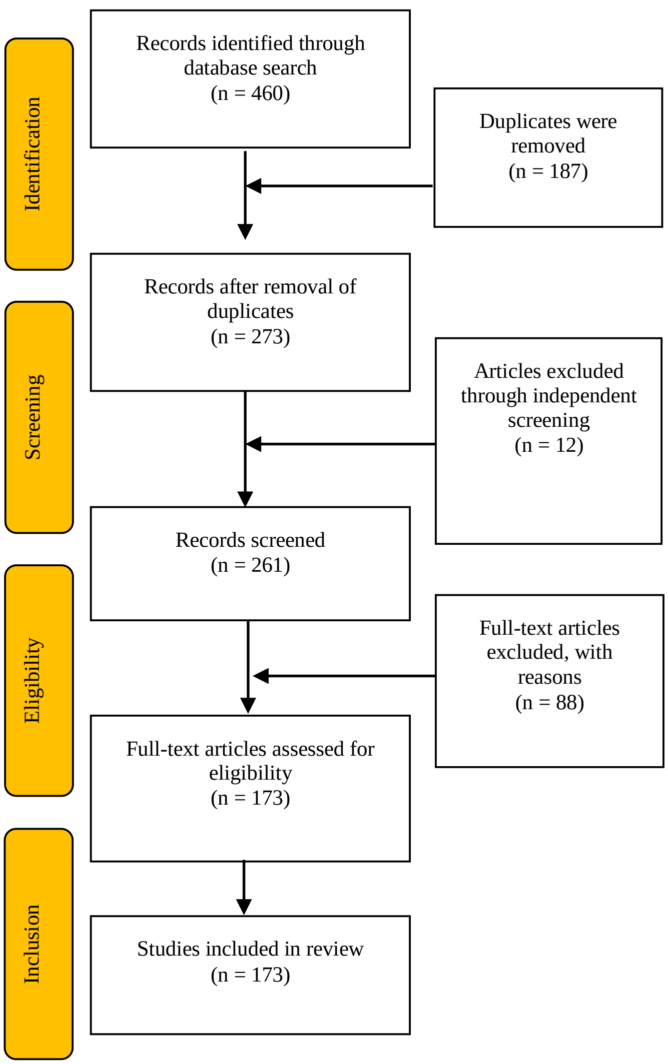

Fig. 1. Flow chart of search process adapted from PRISMA diagram (Adapted from [15]).

III. Results

A. *RQ1: How is Machine Learning Applied for Detecting Fake News in the Health, Political, and Economics Domains?*

This study addressed RQ1 by examining machine learning techniques for detecting fake news and their application across the health, economics, and political domains. Five primary categories of machine learning approaches were reviewed: supervised learning, unsupervised learning, deep learning, ensemble learning, and hybrid approaches.

Fig. 2 illustrates the distribution of the machine learning techniques used in the included studies. Most studies used supervised learning (n = 86 studies), where Support Vector Machine (SVM) was the most widely used method (50 studies), followed by random forest (37 studies), logistic regression (37 studies), and naïve Bayes (35 studies). Deep learning was the second most utilised technique (n = 73 studies), which reflected its increasing importance in addressing fake news detection challenges. Transformer-based models were the most frequently applied deep learning models (45 studies), followed by long short-term memory (LSTM) networks (31 studies) and CNNs (26 studies). Hybrid learning was used in 35 studies and represented a moderately adopted approach. Lastly, ensemble and unsupervised learning were the least used techniques, where each was used in only five studies, which suggested their limited applicability in this context.

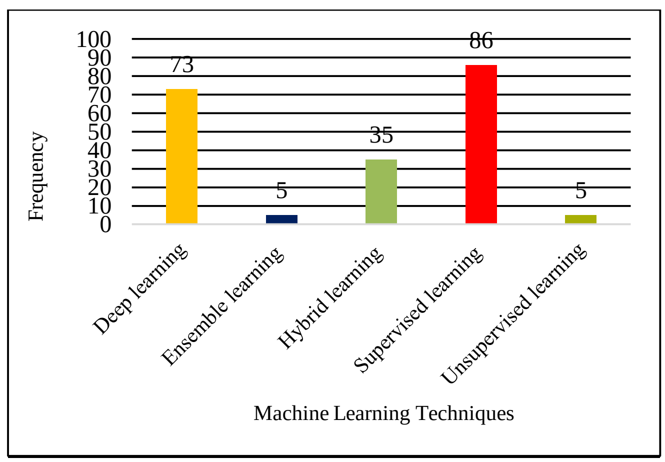

Fig. 2. Distribution of machine learning techniques in reviewed studies.

The review process was enhanced by examining the application of machine learning techniques across the health, economic, and political domains. Fig. 3 highlights that the health sector led in machine learning applications, particularly in deep learning (56 instances) and supervised learning (58 instances), which dominated. For example, studies such as [38, 83, 141] used deep learning models, such as CNNs, LSTM, and bidirectional LSTM (BiLSTM). These advancements have been driven by the increasing availability of medical datasets, which include X-ray images. The accessibility of such data has enabled deep learning models to achieve high accuracy in diagnosing disease, classifying medical images, and predicting patient outcomes. Nevertheless, ensemble learning was rarely applied, with only five instances reported in the health domain.

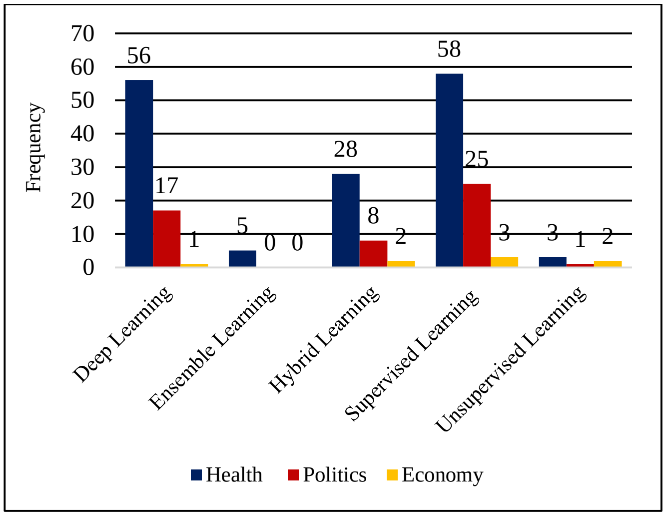

Fig. 3. Usage of machine learning techniques across domains.

The political domain demonstrated a moderate level of machine learning adoption, which was mainly in supervised learning (25 instances), with a smaller but notable use of deep learning (17 instances). Studies in [48, 185] used supervised models, such as Naïve Bayes and SVM to analyse sentiment, detecting political stances, and predicting election outcomes. These models were commonly used due to their effectiveness in processing text-based data, such as social media posts, political speeches, and news articles. In comparison, the economics domain demonstrated limited machine learning adoption. The included studies contained only a few references to deep, hybrid, supervised, and unsupervised learning.

B. *RQ2: What are the Evaluation Metrics Commonly used in the Health, Political and Economic Domain?*

The RQ2 was addressed by examining the evaluation methodologies used in applying machine learning to detect fake news. The commonly used datasets for evaluating the proposed machine learning and the data pre-processing techniques that enhance data quality were explored. The data preparation methods were reviewed to ensure accuracy and reliability, hyperparameter tuning strategies for optimising model performance are discussed, and a comprehensive analysis of the evaluation metrics used to assess model effectiveness is provided.

Fig. 4 presents the most frequently used datasets in fake news detection across health, politics, and economics. The results highlight the prevalence of these datasets in the included studies and the tools designed for identifying fake news. Twitter was the most frequently used dataset, where it was featured in 78 studies by a wide margin. This dominance highlighted the role of Twitter as a major platform in public discussions and real-time misinformation spread. A common research strategy involved manipulating various types of Twitter data, including raw tweet text [25, 55, 85] user IDs [16, 112, 132], tweet and retweet counts [19, 33, 60, 78, 154, 174], likes and reply counts [37, 66, 173], hashtags [54, 64, 78, 123]. Twitter metadata [22, 167, 182], URLs [20, 121], and specific keywords [54, 64, 78].

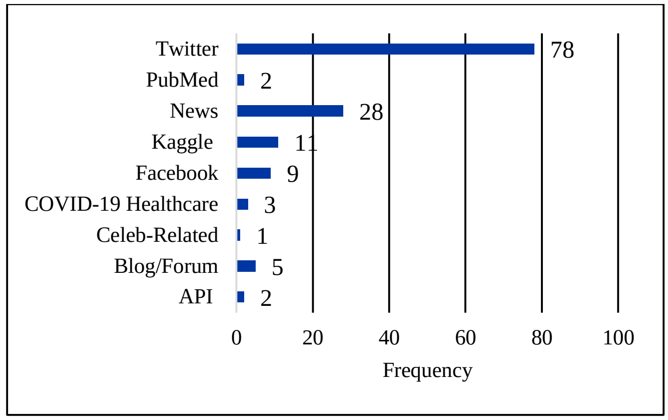

Fig. 4. Commonly used datasets in fake news detection in the included studies.

News datasets were the second most frequently used dataset (n = 28 studies). Their importance lies in their structured format, which typically includes headlines, body text, and publication dates. This structure renders them suitable for text classification and information extraction tasks, including fake news detection. For example, the FakeNewsNet dataset [42, 59, 86, 115], BuzzFeed News [44, 172], and local newspapers such as China Times [106] and The Star [169] were commonly used for analysis.

The third most frequently used dataset was the Kaggle dataset, a machine learning platform (n = 11 studies). Moderately used datasets included Facebook datasets (n = 9 studies) and other sources such as blogs and forums (n = 5 studies). Specialised datasets, including those focused on COVID-19 healthcare misinformation, PubMed, and APIs (used as data collection tools), were used less frequently, appearing in 3 studies [83, 89, 118], 2 studies [84, 178], and 2 studies [40, 181], respectively. Celebrity-related datasets were identified in only one study [150], indicating a niche research area.

Fig. 5 illustrates the frequency of commonly used preprocessing techniques in the included studies. These techniques are important for data preparation to enhance the accuracy and reliability of the proposed machine learning models. Tokenisation was the most frequently used preprocessing technique (n = 77 studies), which highlighted its importance in splitting text into meaningful units for analysis. The included studies used tokenisation in English [55, 60, 116, 145, 153], Chinese characters [18, 100, 102], Arabic [35, 74, 105, 134, 156], Turkish [110, 188], and Korean [78].

The second most common preprocessing technique was stop word removal (n = 68 studies), which highlighted its role in eliminating non-informative words, such as "and" or "the." While stop word removal was mostly used in English, it was also applied in Chinese [18, 69, 100], Brazilian Portuguese [48, 54], Arabic [74, 134] and Urdu [188]. Data filtering was the third most frequently used preprocessing technique (n = 51 studies). The other frequently used techniques were punctuation removal (44 studies) and URL removal (37 studies), which both aimed to reduce noise in textual data. Additionally, lowercasing text and stemming were each used in 33 studies.

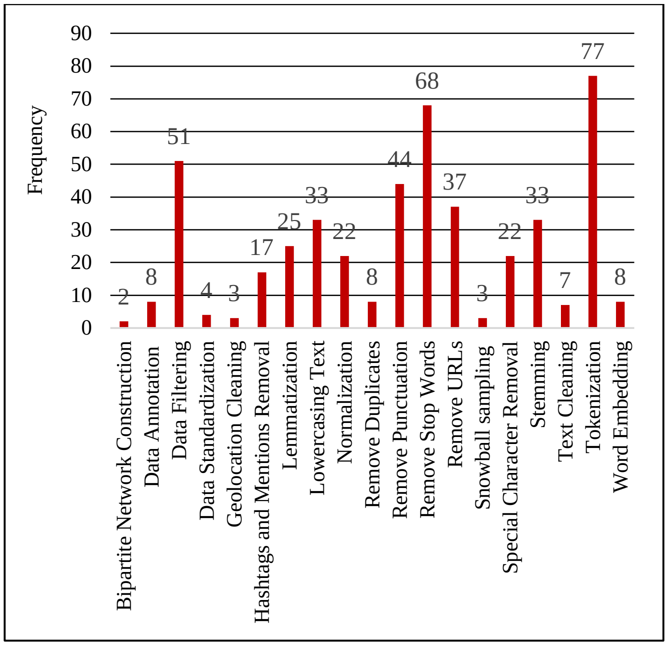

Fig. 5. Commonly used preprocessing techniques in detecting fake news.

The less commonly used preprocessing techniques were lemmatisation (25 studies), normalisation (22 studies), and special character removal (22 studies), which focus on improving text structure and uniformity. Specialised preprocessing steps, such as data annotation, duplicate removal, and word embedding (each, n = 8 studies), were utilised less frequently but were important in certain contexts. Furthermore, the snowball sampling and geolocation cleaning preprocessing techniques were minimally applied (n = 3 studies). Lastly, the least frequently used techniques were data standardisation (four studies) and bipartite network construction (two studies).

This distribution reflected the relative importance and applicability of preprocessing techniques in detecting fake news. Tokenisation, stop word removal, and data filtering were the most critical techniques. Additionally, the choice of preprocessing techniques depends on the dataset language, as different languages require specific methods to handle word forms, writing systems, and grammar.

The data preparation techniques used to evaluate fake news detection models were examined. Fig. 6 demonstrates that data splitting was the most frequently used technique and represented 55% of the methods used. This result emphasises the importance of data splitting in dividing datasets into training and testing subsets to assess model performance. Most of the studies applied 80:20 data splitting [29, 31, 42, 65, 67, 110, 126, 134, 136, 145, 159, 161, 168, 179, 181] and 70:30 data splitting [17, 35, 54, 59, 74, 81, 99, 124, 131, 160] techniques.

Cross-validation was the second most frequently used data preparation technique, representing 37% of the total. This method improves model evaluation by dividing the data into multiple folds and rotating the training and testing phases. For example, 10-fold cross-validation was used in several studies [19, 20, 25, 26, 55, 83, 85, 102, 114, 122, 132, 139, 188] and [22, 48, 97, 117, 130, 173, 184, 186] used five-fold cross-validation. Sampling accounted for 6% of the methods, where stratified sampling [84, 137] was a prominent example. Stratified sampling aids the selection of representative subsets to address class imbalances or reduce dataset size for analysis. The less common techniques were clustering [108, 148] and temporal splitting [128, 147], which each represented 1% of the methods.

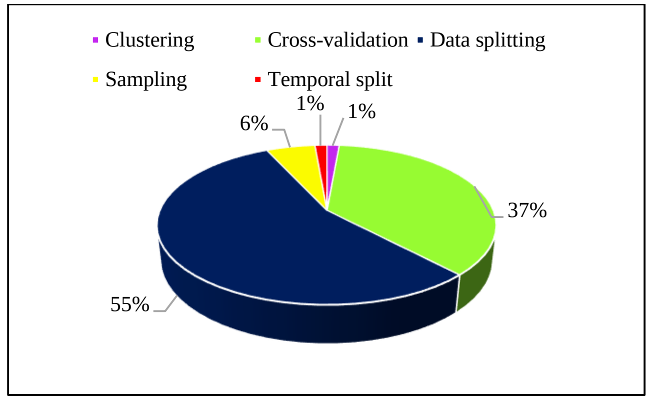

Fig. 6. Data preparation techniques for evaluation in fake news detection models.

Fig. 7 illustrates the frequency of the classification metrics used to evaluate the performance of the fake news detection models. Accuracy was the most frequently used metric (n = 116 studies), followed by precision and recall (n = 109 and 103 studies, respectively), which highlighted their importance in assessing prediction quality and true positive detection. The F1-score, which is a harmonic mean of precision and recall, was applied in 108 studies, which emphasised its role in balancing these two measures. Contrastingly, specificity and the Matthews correlation coefficient (MCC) were less commonly used (n = 3 studies). Receiver operating characteristic (ROC) curve and area under the curve (AUC) metrics were reported in 28 studies, which underscored their usefulness in evaluating classification performance across varying thresholds.

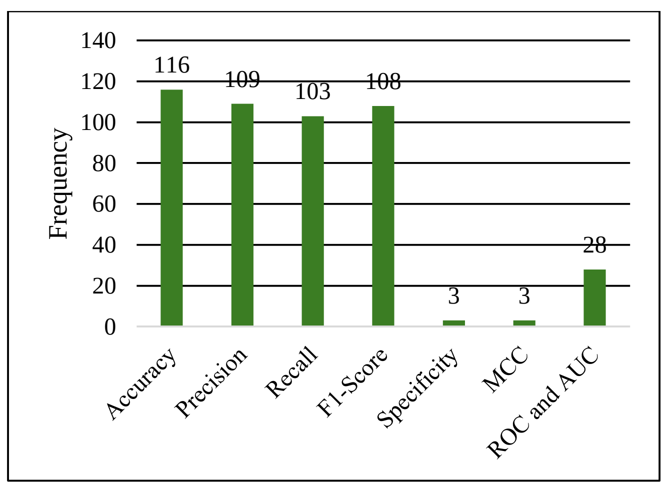

Fig. 7. Classification metrics used for evaluating fake news detection models.

C. RQ3: What are the Key Trends, Challenges, and Future Directions in the Health, Political, and Economics Domains?

The RQ3 was addressed by examining the key trends, challenges, and future directions across the health, political, and economics domains. Fig. 8 illustrates the machine learning technique use trends (deep learning, ensemble learning, hybrid learning, supervised learning, and unsupervised learning) between 2017 and 2024. Deep learning and supervised learning usage increased steadily from 2017 and peaked in 2021.

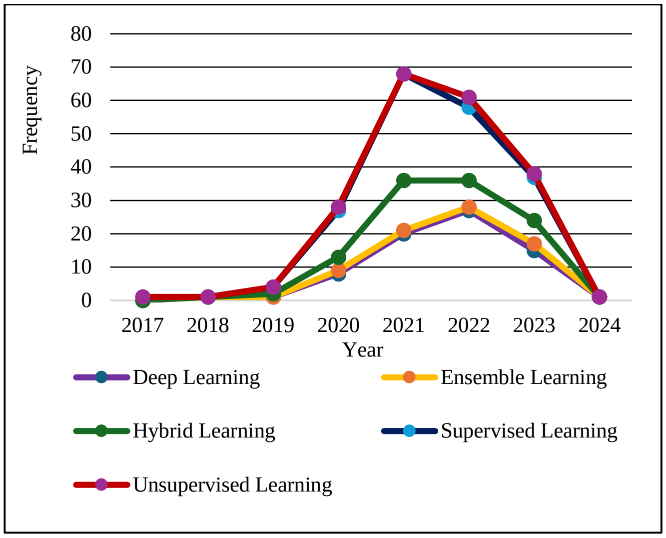

Fig. 8. Machine learning techniques trend over time.

Deep Learning usage frequency was highest at approximately 75 instances. Nonetheless, both techniques experienced a decline after 2022. Hybrid learning gained traction in 2019, peaked in 2021 (40 instances), and then its usage declined in subsequent years. Similarly, unsupervised learning grew significantly from 2019 and peaked in 2022 (60 instances) before decreasing. Contrastingly, ensemble learning demonstrated modest growth, where it peaked in 2021 but maintained a consistently lower frequency compared to the other techniques. The graph highlighted that the adoption of machine learning techniques increased significantly beginning in 2017, with most methods peaking between 2021 and 2022, followed by a noticeable decline in 2023 and 2024. This trend suggested that the use of these techniques either stabilised as research matured or shifted toward new approaches and alternative methodologies.

Fig. 9 presents the challenges of applying machine learning across various domains, which are categorised into six areas. Dataset issues were the most common challenge (124 instances), which highlighted concerns regarding data quality, availability, and relevance in machine learning applications. Contrastingly, ethical concerns were the least reported concern (n = 1 study), while interpretability issues, which relate to understanding and explaining model decisions, were recorded in two instances. Model-related bias, which affects fairness and accuracy, appeared eight times and indicated a moderate level of concern. Handling rapid data evolution was a challenge cited twice, which reflected the occasional challenges in maintaining up-to-date models. Platform-specific issues, which involved technical barriers or limitations in specific machine learning platforms, were reported in seven studies. Overall, dataset issues dominated the challenges significantly and highlighted the need for robust and relevant data, while other challenges were observed less frequently.

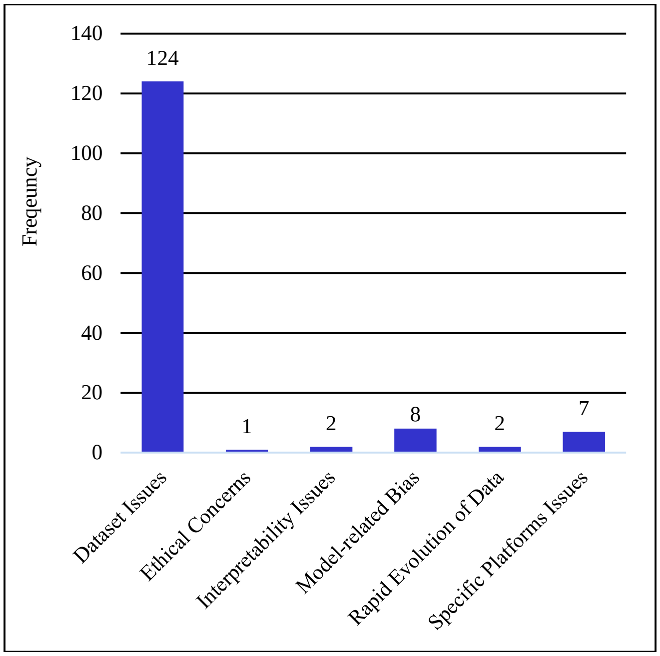

Fig. 9. Distribution of machine learning challenges across domains.

Fig. 10 highlights the key future research directions in machine learning, which are categorised into five areas. Data expansion, which involves increasing and diversifying data was the most prominent area (n = 22 studies), followed by theory exploration, which is aimed on investigating underlying principles and frameworks (n = 18 studies). Fourteen studies mentioned methodology, which involves refining and enhancing machine learning techniques. Eight studies mentioned audience or context analysis, which focuses on understanding the audience and contextual factors and indicated moderate representation.

Contrastingly, technology development, which relates to machine learning technological advancements, was mentioned least frequently (n = 2 studies). Overall, the data expansion, theory exploration, and methodology improvement as major future research focus areas, while audience or context analysis and technology development received comparatively less attention.

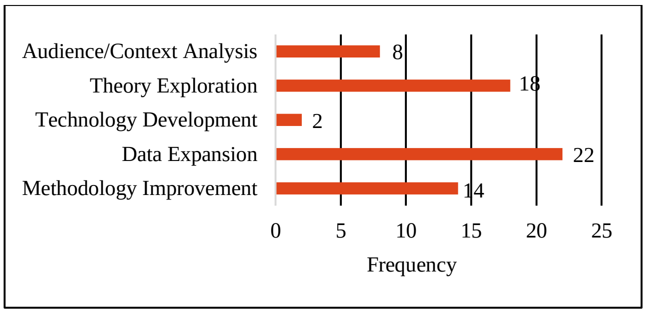

Fig. 10. Future research directions in machine learning.

IV. Discussion

This review highlighted the dominance of the supervised and deep learning approaches, particularly in the health domain. The two approaches recorded the highest application frequency and exhibited domain-specific patterns. This trend highlighted the urgent need for effective misinformation detection mechanisms in health-related contexts, especially during crises, such as the COVID-19 pandemic, where accurate information dissemination is critical. The political domain demonstrated moderate machine learning adoption, which focused primarily on election misinformation. The economics domain had minimal engagement with machine learning, which suggested significant potential. These results revealed an imbalanced focus across the three domains and emphasized the need to expand research into under-represented areas, such as economic misinformation.

The prevalence of supervised and deep learning highlighted their leading role in detecting fake news (86 and 73 instances, respectively). The extensive use of supervised learning can be attributed to its simplicity and adaptability, particularly when labelled datasets are available. Deep learning has emerged as a powerful tool as it can process large datasets and capture complex patterns in textual and multimedia data, especially within the health domain. Hybrid approaches were less frequent (n = 35 studies) but were promising approaches that integrated the strengths of different methodologies. Contrastingly, the limited use of unsupervised and ensemble learning highlighted the need for innovation in using these techniques for unlabeled and heterogeneous data sources.

The dominance of Twitter datasets (n = 78 studies) highlighted the influence of the platform in misinformation analysis. Real-time interactions in Twitter, broad user engagement, and accessible API render it a valuable resource for studying misinformation trends, virality, and public response. Nevertheless, this reliance raises concerns about dataset bias, as Twitter does not fully represent online discourse across all demographics. Expanding research to other platforms, such as Facebook, TikTok, and WhatsApp can yield a more comprehensive understanding of fake news dissemination across different digital ecosystems. Nonetheless, the underutilization of domain-specific datasets, such as PubMed and COVID-19 healthcare datasets, suggested missed opportunities to develop specialized detection tools.

Dataset-related challenges were the most significant barrier in misinformation research, where 124 studies highlighted issues regarding data quality, availability, and representativeness. These challenges were evident in the health and political domains, where misinformation evolves rapidly. Health misinformation spreads quickly, especially during crises, such as pandemics, as false claims regarding treatments, vaccines, and diseases frequently emerge. Similarly, political misinformation shifts due to elections, policy changes, and global events and require continuous updates to detection models. Enhancing the accuracy and effectiveness of misinformation research requires up-to-date and diverse datasets. Outdate or biased data can lead to inaccurate predictions and reduce generalizability. Hence, ensuring high-quality, representative datasets is essential for improving model performance and effectively detecting fake news across different platforms and contexts.

The fake new detection models widely used evaluation metrics (accuracy, precision, recall, and F1-score), which reflected their reliability in assessing performance. Nevertheless, these metrics may not always provide a complete picture, especially in imbalanced datasets, where fake news instances are significantly outnumbered by real news. Less commonly used metrics (MCC and AUC-ROC) can provide deeper insights by accounting for class imbalances and assessing model discrimination ability. Incorporating these additional metrics can improve machine learning model evaluation and ensure a more comprehensive understanding of their effectiveness in detecting misinformation.

The temporal trends indicated that the adoption of machine learning techniques for detecting fake news peaked between 2021 and 2022, and declined in 2023 and 2024. This decline suggested that research in this area is either stabilizing (existing models are maturing) or shifting toward alternative approaches (hybrid models, explainable artificial intelligence, or ethical considerations in misinformation detection). Interest in hybrid and unsupervised learning approaches has grown since 2019, particularly where labelled data is scarce. Nonetheless, limited attention to ethical concerns and interpretability has highlighted the gaps in ensuring fairness and transparency in machine learning models. Future research should address these challenges by prioritizing theoretical advancements, methodology refinement, and dataset expansion, especially in underrepresented domains. Additionally, enhancing model interpretability and mitigating bias will be crucial for enhancing trust, fairness, and real-world applicability in detecting misinformation.

There were minimal reports of ethical concerns and interpretability issues, which were cited in one and two studies, respectively. This result highlighted a significant gap in addressing the broader implications of machine learning models in detecting fake news, particularly in the health and politics domains. The future research directions identified in this review emphasized the need for theory exploration (22 studies) and methodology improvement (20 studies). Dataset expansion and diversification (19 studies) was another critical area, especially in under-represented domains, such as economics. Context analysis and technology development received comparatively less attention, which highlighted opportunities for further interdisciplinary research and technological advancements.

V. Conclusion

Machine learning has become essential in combating misinformation. This SLR critically examined the role of machine learning techniques in detecting fake news across the health, political, and economics domains. Supervised learning was the most commonly used approach as it is effective in environments with high-quality labelled data. Deep learning techniques excel at extracting nuanced features from complex data structures, which rendered them valuable in the dynamic landscape of fake news detection. The hybrid, ensemble, and unsupervised learning techniques were underutilised, which presented opportunities for future research directions. The analysis revealed an uneven research focus distribution, with health-related misinformation receiving the most attention, while political and economic fake news remained less explored. The results underscored the need for more targeted explorations in these areas. Data quality issues, model bias, and ethical concerns highlighted the necessity of bias-mitigating algorithms and improved interpretability to enhance trust in these technologies. Machine learning application frequency in detecting fake news peaked in 2021–2022, and then stabilised, which suggested that while the field is maturing, further methodological and theoretical advancements are needed. Despite the widespread use of datasets, such as Twitter, specialised resources (PubMed) lack engagement, which could enhance detection capabilities in domain-specific misinformation. While accuracy, precision, and recall are commonly used evaluation metrics, incorporating broader measures (MCC and AUC-ROC) could assess model performance more comprehensively. Future research can explore unsupervised and semi-supervised learning methods, which require less human intervention and adapt more efficiently to evolving misinformation. Additionally, the under-representation of machine learning in economic fake news detection is a critical area for exploration. In conclusion, while using machine learning to detect fake news has progressed significantly, continuous research is essential to address emerging challenges and adapt to the rapidly evolving digital landscape. Ensuring information credibility is vital for public trust and safety and requires constant technological advancements to counter misinformation effectively.

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APPENDIX A

Author(s)	Research Type	Database	Year
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